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The impact of Artificial Intelligence on Managerial Decision- Making:  
A Strategic Analysis of opportunities and Challenges for Data -Driven  
Governance and Management.

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## Abstract

The purpose of the dissertation is to examine the impact of Artificial Intelligence (AI) on managerial decision-making, focusing on the opportunities, challenges, and governance implications associated with AI-supported decision environments. The significant progress on AI tools forced organizations to adopt AI technologies to enhance analytical capability and strategic responsiveness, in order to understand how these systems influence the effectiveness on decision making and on responsibility within the organizations. AI tools in management field have become a critical research priority. This study follows a qualitative dominant research approach. Data were collected through semi structured interviews with professionals working in AI enabled organizations. In addition, a comparative case analysis was conducted to examine organizations that adopt AI-driven decision-making tools across different industries. The findings of the research indicate that Artificial Intelligence plays a crucial role in accelerating decision making, enhancing forecasting and accuracy, and making analytical process less complicated. In complex and data intensive environments the ability in using AI will make a huge difference in corporate world. However, only technological capability does not guarantee more reliable decision outcomes. Instead, if organizations can intergrade AI, depends also on governance maturity, the trust on managers, transparency on procedures and a well-structured Human and AI collaboration. The Hybrid decision models, in which AI systems offer analytical support to executive managers withholding final decision authority, seems to be the most effective approach in order to achieve not only an improvement in performance but also to ensure more reliable results and better accountability rates among managers.

Based on the empirical findings, the study suggests a mixed AI Decision Governance Framework. The empirical findings suggest that governance maturity plays an important organizational role in the relationship between technological potential and decision effectiveness. In particular, the maturity within Governances can be the crucial factor that enables organizations to better exploit AI technologies and produce more effective decision-making processes. In addition, this research proposes the conceptual AI Decision Effectiveness and Assurance Index (AI-DEAI) as a combined evaluation framework. The model evaluates multiple dimensions, including decision performance,

trust and explainability, governance and accountability, human–AI collaboration, organizational readiness. Furthermore, the study proposes the Decision Safety Differential metric, which provides a mechanism for evaluating whether the adoption of AI can improve decision related risk outcomes as opposed to environments that decisions are made solely from humans.

The study offers to academic literature by combining decision -making theory, socio-technical systems theory, governance research, and augmented intelligence perspectives. These elements are integrated into a unite conceptual model that explains AI-enabled managerial decision environments. From a managerial perspective, the findings offer practical insights for organizations that aim to implement AI in a responsible way while improving decision performance and maintaining organizational accountability.

Overall, the study suggests that sustainable AI adoption depends on the alignment between technological capabilities, governance structures, and human oversight within modern organizations.

**Keywords:** *Artificial Intelligence, Managerial Decision-Making, AI Governance, Human–AI Collaboration, Decision Effectiveness*

## Περίληψη

Ο σκοπός της παρούσας διπλωματικής εργασίας είναι να εξεταστεί η επίδραση της Τεχνητής Νοημοσύνης (Artificial Intelligence) στη διαδικασία λήψης αποφάσεων σε θέματα διοίκησης εστιάζοντας στις ευκαιρίες τις προκλήσεις και τις επιπτώσεις στη διοίκηση που συνδέονται με κέντρα λήψης αποφάσεων, τα οποία υποστηρίζονται από συστήματα Τεχνητής Νοημοσύνης. Η αξιοσημείωτη πρόοδος των εργαλείων τεχνητής νοημοσύνης έχει αναγκάσει τους οργανισμούς να εντάξουν τεχνολογικά συστήματα ΤΝ, έτσι ώστε να ενισχύσουν τις ικανότητες ανάλυσης με στόχο την θωράκιση της διοικητικής τους ικανότητας και της στρατηγικής τους ανταπόκρισης, ώστε να γίνει κατανοητό πως τα συστήματα τεχνητής νοημοσύνης εμπλέκονται στην αποτελεσματικότητα λήψης αποφάσεων και την απόδοση ευθυνών μέσα στους οργανισμούς. Η σημαντική εξέλιξη των εργαλείων τεχνητής νοημοσύνης σε θέματα

διοίκησης έχει αποτελέσει σημαντική προτεραιότητα στον τομέα έρευνας και ανάπτυξης των εταιρειών.

Η παρούσα διπλωματική εργασία προσεγγίζει την έρευνα με μια αναλυτική προσέγγιση που βασίζεται κυρίως σε ποιοτικά δεδομένα. Η συλλογή δεδομένων έγινε μέσω ημιδομημένων συνεντεύξεων με στελέχη επιχειρήσεων που εργάζονται σε εταιρείες, οι οποίες εφαρμόζουν εργαλεία τεχνητής νοημοσύνης. Επιπρόσθετα έγινε συγκριτική ανάλυση σε παραδείγματα οργανισμών, οι οποίοι υιοθέτησαν εργαλεία λήψης αποφάσεων που βασίζονται στην τεχνητή νοημοσύνη σε διαφορετικούς τομείς.

Η έρευνα ανέδειξε ευρήματα ότι η τεχνητή νοημοσύνη διαδραματίζει καθοριστικό ρόλο στην επιτάχυνση της λήψης αποφάσεων σε σύνθετα περιβάλλοντα και στη βελτίωση της πρόβλεψης μέσω της μείωσης της πολυπλοκότητας των αναλυτικών διαδικασιών. Σε περιβάλλοντα που υπάρχει υψηλή πολυπλοκότητα και εκτεταμένη χρήση δεδομένων, η ικανότητα αξιοποίησης της τεχνητής νοημοσύνης μπορεί να διαδραματίσει καθοριστικό ρόλο για τους οργανισμούς. Ωστόσο, η τεχνολογική ικανότητα από μόνη της δεν εγγυάται πιο αξιόπιστα αποτελέσματα στη λήψη αποφάσεων. Η αποτελεσματική ενσωμάτωση της τεχνητής νοημοσύνης εξαρτάται επίσης από το επίπεδο ωριμότητας της διακυβέρνησης στο οργανωτικό επίπεδο, την εμπιστοσύνη των διοικητικών στελεχών στην τεχνητή νοημοσύνη, τη διαφάνεια των διαδικασιών και την αποτελεσματική συνεργασία μεταξύ ανθρώπου και τεχνητής νοημοσύνης.

Η πιο αποτελεσματική προσέγγιση φαίνεται να είναι τα υβριδικά μοντέλα λήψης αποφάσεων, τα οποία προσφέρουν στα στελέχη αναλυτική υποστήριξη κατά την διαδικασία λήψης αποφάσεων, αλλά η τελική ευθύνη της απόφασης παραμένει στους ανθρώπους. Με αυτόν τον τρόπο, τα εργαλεία τεχνητής νοημοσύνης, βοηθούν όχι μόνο στο να βελτιωθεί η απόδοση τους, αλλά και στην εξασφάλιση πιο αξιόπιστων αποτελεσμάτων και μεγαλύτερης απόδοσης ευθύνης μεταξύ των διοικητικών στελεχών.

Με βάση τα εμπειρικά ευρήματα, η διατριβή προτείνει μια σύνθεση διακυβέρνησης λήψης αποφάσεων από τους ανθρώπους με χρήση τεχνητής νοημοσύνης (AI Decision Governance Framework). Τα αποτελέσματα τονίζουν τον βαθμό ωριμότητας της διακυβέρνησης ως κρίσιμο παράγοντα στην οργάνωση της σχέσης των τεχνολογικών εργαλείων και της αποτελεσματικότητας των αποφάσεων. Συγκεκριμένα, το επίπεδο

ωριμότητας των μηχανισμών διακυβέρνησης μπορεί να αποτελέσει καθοριστικό παράγοντα που επιτρέπει στους οργανισμούς να αξιοποιήσουν αποτελεσματικότερα τις τεχνολογίες τεχνητής νοημοσύνης και να επιτύχουν πιο αποτελεσματικές διαδικασίες λήψης αποφάσεων.

Επιπλέον, η διπλωματική προτείνει τον θεωρητικό δείκτη TN Αποτελεσματικότητας και διασφάλισης αποφάσεων (AI-DEAI) ως ένα σύνθετο πλαίσιο αξιολόγησης. Το μοντέλο αξιολογεί πολλαπλές διαστάσεις, όπως την απόδοση των αποφάσεων, τα ζητήματα κινδύνου και ασφάλειας, το επίπεδο ανάπτυξης της οργανωτικής διακυβέρνησης, τα κύρια συστήματα τεχνητής νοημοσύνης καθώς και την αποτελεσματικότητα της συνεργασίας μεταξύ διοικητικών στελεχών και συστημάτων τεχνητής νοημοσύνης.

Επιπλέον, η μελέτη προτείνει τον θεωρητικό δείκτη TN διαφορικής ασφάλειας αποφάσεων, ο οποίος παρέχει έναν μηχανισμό αξιολόγησης για το κατά πόσο η υιοθέτηση της τεχνητής νοημοσύνης μπορεί να βελτιώσει τα αποτελέσματα που σχετίζονται με τον κίνδυνο στη λήψη αποφάσεων σε σύγκριση με περιβάλλοντα όπου οι αποφάσεις λαμβάνονται αποκλειστικά από ανθρώπους.

Η έρευνα συμβάλλει στην ακαδημαϊκή βιβλιογραφία συνδυάζοντας τη θεωρία λήψης αποφάσεων, τη θεωρία κοινωνικοτεχνικών συστημάτων, την έρευνα για τη διακυβέρνηση και τις προσεγγίσεις της επαυξημένης νοημοσύνης. Τα στοιχεία αυτά ενσωματώνονται σε ένα ενιαίο εννοιολογικό μοντέλο που εξηγεί τα περιβάλλοντα διοικητικής λήψης αποφάσεων με χρήση τεχνητής νοημοσύνης.

Από διοικητική σκοπιά, με τα ευρήματα δίνονται πρακτικές κατευθύνσεις για οργανισμούς που επιδιώκουν να εφαρμόσουν την τεχνητή νοημοσύνη με υπεύθυνο τρόπο, βελτιώνοντας παράλληλα την απόδοση των αποφάσεων και διατηρώντας υψηλά επίπεδα οργανωτικής ευθύνης.

Συνολικά, η έρευνα καταδεικνύει ότι η βιώσιμη υιοθέτηση της τεχνητής νοημοσύνης εξαρτάται από την ευθυγράμμιση μεταξύ τεχνολογικών δυνατοτήτων, δομών διακυβέρνησης και ανθρώπινης εποπτείας στο πλαίσιο των σύγχρονων οργανισμών.

***Λέξεις-κλειδιά:** Τεχνητή Νοημοσύνη, Διοικητική Λήψη Αποφάσεων, Διακυβέρνηση AI, Συνεργασία Ανθρώπου-AI, Αποτελεσματικότητα Αποφάσεων*

## Περιεχόμενα

|                                                                                              |    |
|----------------------------------------------------------------------------------------------|----|
| 1.1 The Evolution of Artificial Intelligence in Organizational Decision-Making .....         | 8  |
| 1.2 From Decision Support Systems to AI-Driven Decision Intelligence.....                    | 10 |
| 1.3 Opportunities Created by AI-Driven Decision-Making .....                                 | 11 |
| 1.4 The Growing Importance of AI Governance in Decision-Making .....                         | 12 |
| 1.5 Research Gap .....                                                                       | 14 |
| 1.6 Research Aim and Objectives .....                                                        | 15 |
| 1.7 Research Questions .....                                                                 | 16 |
| 1.8 Significance of the Study .....                                                          | 17 |
| 1.9 Chapter Conclusion.....                                                                  | 18 |
| 2.1 Artificial Intelligence as a Core Driver of Organizational Decision Transformation ..... | 19 |
| 2.2 Evolution from Automation to Human–AI Collaborative Decision Models .....                | 21 |
| 2.3 Managerial Decision-Making Theory and Cognitive Perspectives.....                        | 22 |
| 2.4 Opportunities of AI in Managerial Decision-Making .....                                  | 26 |
| 2.5 Challenges and Risks of AI-Driven Decision Environments .....                            | 28 |
| 2.6 The Role of Trust, Transparency, and Leadership in Human–AI Decision Systems.....        | 29 |
| 2.7 Socio-Technical Perspective on AI Adoption.....                                          | 31 |
| 2.8 AI Governance and Responsible AI Frameworks .....                                        | 32 |
| 2.9 Research Gap and Conceptual Positioning of the Study .....                               | 34 |
| 2.10 Chapter Summary.....                                                                    | 34 |
| 3.1 Research Philosophy.....                                                                 | 35 |
| 3.2 Research Design and Approach .....                                                       | 36 |
| 3.3 Data Collection Methods.....                                                             | 37 |
| 3.3.1 Primary Data Collection — Semi-Structured Interviews .....                             | 37 |
| 3.3.2 Interview Guide Structure .....                                                        | 38 |
| 3.3.3 Case Study Selection and Secondary Data Sources .....                                  | 39 |
| 3.4 Sampling Strategy .....                                                                  | 39 |
| 3.5 Research Strategy Justification .....                                                    | 40 |
| 3.6 Data Analysis Methodology.....                                                           | 41 |
| 3.7 Interview Analysis and Coding Framework .....                                            | 42 |
| 3.8 Reliability and Validity .....                                                           | 43 |
| 3.9 Ethical Considerations .....                                                             | 43 |

|                                                                                        |    |
|----------------------------------------------------------------------------------------|----|
| 3.10 Methodological Limitations .....                                                  | 44 |
| 4.1 Introduction .....                                                                 | 46 |
| 4.2 AI and Decision Performance Transformation .....                                   | 46 |
| 4.3 Trust Formation and the Role of Explainability .....                               | 47 |
| 4.4 Emerging AI Governance Practices .....                                             | 48 |
| 4.5 Human–AI Collaboration and Decision Authority Distribution .....                   | 49 |
| 4.6 Case Study .....                                                                   | 49 |
| 4.6.1 Amazon.....                                                                      | 49 |
| 4.6.2 COMPAS.....                                                                      | 53 |
| 4.6.3 Case Study Netflix.....                                                          | 56 |
| 4.7 Cross-Theme Analytical Integration.....                                            | 60 |
| 5.1 Introduction .....                                                                 | 63 |
| 5.2 Interpretation of Findings in Relation to Decision-Making Theory .....             | 63 |
| 5.3 Trust, Transparency and Explainability in AI-Supported Decision Environments ..... | 64 |
| 5.4 Governance Maturity and Ethical Decision Integration .....                         | 65 |
| 5.5 Human–AI Collaboration and Decision Authority Structures.....                      | 66 |
| 5.6 AI Decision Governance Framework .....                                             | 67 |
| 5.7 AI Decision Effectiveness and Assurance Index (AI-DEAI).....                       | 69 |
| 5.7.1 Conceptual Rationale.....                                                        | 69 |
| 5.7.2 Structure of the AI Decision Effectiveness and Assurance Index.....              | 70 |
| 5.7.3 Dimension 1 Decision Performance Quality (DPQ) .....                             | 71 |
| 5.7.4 Dimension 2 Trust, Transparency, and Explainability (TTE) .....                  | 72 |
| 5.7.4.1 Decision Safety Differential (DSD) .....                                       | 73 |
| 5.7.5 Dimension 3 Governance Accountability (GA) .....                                 | 73 |
| 5.7.6 Dimension 4 Human–AI Collaboration Effectiveness (HACE) .....                    | 74 |
| 5.7.7 Dimension 5 Organizational Readiness (OR) .....                                  | 74 |
| 5.7.8 Composite Index Structure .....                                                  | 75 |
| 5.7.9 Theoretical Contribution .....                                                   | 76 |
| 5.7.10 Managerial Application.....                                                     | 76 |
| 5.7.11 Research Implications .....                                                     | 77 |
| 5.8 Final Conclusions .....                                                            | 77 |
| REFERENCES .....                                                                       | 79 |
| Δήλωση Συγγραφέα.....                                                                  | 81 |

## 1.1 The Evolution of Artificial Intelligence in Organizational Decision-Making

The rapid evolution of Artificial Intelligence (AI) over the past decade transformed gradually from a complex analysis tool into a crucial component of organizational strategy and managerial decision-making processes. Even more organizations all over the world in many fields and industries rely on AI centered systems in order to support activities such as optimization in operations and in planning through key strategy areas, customer data analysis, and risk assessment. This development has been supported by the rapid growth of data availability, significant advances in machine learning algorithms, and the expanding capabilities of predictive analytics technologies that allow organizations to extract insights from complex data environments (Soori et al., 2024; Ravi et al., 2025).

Empirical studies indicate that the adoption of AI can improve organizational decision-making performance in several ways. AI-supported decision systems allow firms to analyze large volumes of data, identify patterns more efficiently, and support faster and more accurate decision processes. Research across different industries suggests that organizations implementing AI technologies often experience improvements in decision speed, forecasting accuracy, and resource allocation efficiency (Soori et al., 2024). The finding of these studies suggests that companies by adopting AI, are not limited only on gradually improve their operations but can also reform how companies process data and taking strategic decisions.

Strategic managers perspective on AI, is gradually viewed not only as an automation tool but as an opportunity that supports the decisions taken by humans. The purpose of AI systems is not to replace managerial judgment but to support managers in processing vast amount of information and identifying patterns that are difficult to spot through classic analytical methods. This interpretation aligns with resource-based and dynamic capability perspectives, which highlight that advanced analytics and AI capabilities can become strategic assets when effectively integrated into organizational processes.

Academic literature also indicates that through AI technologies, decision effectiveness can be enhanced because if we can automatize repetitive analytical tasks we can reduce certain forms of cognitive bias making insight process faster. However, technological capability alone does not guarantee successful outcomes. Organizational factors such as leadership support, governance mechanisms, organizational culture, and employee readiness significantly influence how effectively AI contributes to decision quality (Papagiannidis et al., 2025; Ransbotham et al., 2023). This strengthens the point of view that AI adoption could transform the technologies used by companies rather than a purely technological substitution in operational management.

The recent management approach is moving from intuition driven decision models to more data driven and practices based on evidence by integrating AI into managerial decision procedures. In increasingly dynamic and uncertain environments, AI systems help organizations respond more effectively to market changes, operational disruptions, and evolving stakeholder expectations. In this sense, AI functions not only as a decision-support technology but also as a mechanism that transforms how organizations interpret information and manage uncertainty.

In addition, AI can contribute to organizational learning and innovation breakthrough by enabling experimentation, simulation, and predictive scenario analysis. Experiments that are supported by AI may help companies to evaluate alternative strategies with fewer risk and cost. That could accelerate innovation procedures and could improve the company's adaptability. Consequently, AI is widely considered an important driver of long-term organizational performance and competitive advantage.

Overall, in the context of this study AI evolution in decision making among companies shows a shift from traditional analysis support tools toward more complex decision artificial intelligence environments. where human expertise and algorithmic insights interact through the whole process. This transition reflects the fast integration of AI systems into the core of organizations in decision making field, moving further from supporting roles toward more auto and collaborative functions (Papagiannidis, 2025). While this transformation creates significant opportunities for improving organizational performance, it also introduces new challenges related to governance, accountability and trust in AI-enabled decision environments. In particular, the growing reliance on AI within decision making systems creates critical concerns regarding, responsibility

and the trust establishment between managers and AI on business intelligence systems (Lahusen et al., 2024). These tensions between technological capability and governance requirements form a central focus of the present dissertation.

## 1.2 From Decision Support Systems to AI-Driven Decision Intelligence

The progress of artificial intelligence technologies in decision making caused a big progress and an increase in reliance of organizations on computer intelligence to support the judgment of managers. Companies designed early Decision Support Systems (DSS) to support the data process and help managers making structured decisions by using rule based analytical models. These systems enabled managers to analyze organizational data and improve operational decision quality. However, traditional DSS architectures were limited in their ability to process large volumes of unstructured data and address complex, uncertain decision environments.

The appearance of artificial intelligence (AI) has made companies using more adaptive decision-making intelligence and less static analytical tools, because are capable of learning from data and continuously improving performance. The systems that use AI for making decisions, rely more on machine learning algorithms that can identify better the hidden patterns, detect anomalies and produce predictions and insights in real time. These developments enable organizations to integrate data processing, predictive modelling, and algorithmic reasoning into unified decision ecosystems (Ravi et al., 2025; Soori et al., 2024; Pathirannehelage, 2025).

The analysis conducted in this study indicate that decision systems using AI could enhance the objectivity of decisions by reducing certain cognitive biases related to human judgment. Nevertheless, the effectiveness of these systems depends significantly on factors such as transparency, interpretability, and organizational trust. In this context, Explainable Artificial Intelligence (XAI), systems that can plainly explain how they decide, has emerged as a critical component for improving managerial confidence and supporting responsible AI adoption in high-impact decision environments (Kostopoulos et al., 2024; Knapič et al., 2021; De Silva et al., 2025).

Moreover, the most recent research presenting AI as a tool that can augment the ability in decision making rather than replacing the managers. The hybrid human-AI decision

systems have the ability to process large amounts of data and give better analytical depth, while managers can grasp better contextual ideas, ethical problems, and strategic analysis. This complementary interaction supports more balanced and effective decision outcomes (Baird and Maruping, 2021; Pathirannehelage, 2025).

The empirical evidence of the study further indicates that the structure of the governance plays an important role in making AI implementation more successful. Companies that establish mechanisms for better accountability processes, where humans are more active in decision making, and regulatory alignment practices are more likely to achieve reliable and responsible AI integration. Consequently, successful AI adoption depends not only on technological sophistication but also on the maturity of organizational governance frameworks (Jean & Le Pera, 2025).

The collaboration between human cognitive and machine intelligence is often described as augmented intelligence. As organizations increasingly operate in complex strategic environments, algorithmic outputs must be interpreted within broader organizational, cultural, and ethical contexts. These dynamics highlight the growing importance of governance, trust, and human–AI collaboration as central dimensions of contemporary decision-making systems (Kostopoulos et al., 2024; De Silva, Halloluwa and Vyas, 2025; Pathirannehelage, 2025).

## 1.3 Opportunities Created by AI-Driven Decision-Making

The study indicates that when we combine artificial intelligence with managerial decision processes many opportunities are created, not only in refinement operational systems. Because the companies operate in data intensive and environments that always change, AI can be more responsive in new forms of complex decisions and predict outcomes with better accuracy. These opportunities collectively contribute to the transformation of organizational decision architectures and managerial practices (Soori, Arezoo and Dastres, 2024;).

The most important advantage in adopting AI, is that can intergrade the analytical capability with acceleration speed on decisions. AI systems are capable of processing large volumes of structured and unstructured data at speeds unattainable by human analysts, enabling organizations to respond more effectively to market fluctuations,

operational disruptions, and evolving customer behavior patterns. This capability is particularly valuable in environments characterized by uncertainty and time-sensitive decision requirements (Ravi et al., 2025; Dwivedi et al., 2023).

The predictive accuracy and the detection of markets risk can be handled better by AI. Machine learning models can identify emerging trends, detect anomalies, and anticipate potential operational or financial risks earlier than traditional analytical approaches. Improved forecasting capability supports more informed strategic planning and risk management decisions (Kostopoulos et al., 2024; Brynjolfsson, Li and Raymond, 2023).

In addition, by using innovation in learning process the companies can simulate alternative strategic scenarios and evaluate the potential outcomes with lower cost and risk. This capability enhances organizational adaptability by enabling continuous learning from data-driven insights (Dwivedi et al., 2023; Soori, Arezoo and Dastres, 2024).

From a strategic perspective, AI is increasingly recognized as a resource capable of generating sustained competitive advantage. By improving decision quality and enabling real-time monitoring of performance, AI supports more adaptive strategic decision making and enhances organizational responsiveness to environmental changes (Brynjolfsson, Li and Raymond, 2023;).

Overall, these opportunities indicate that AI is evolving into a central driver of organizational transformation rather than merely a tool for automation. However, the realization of these benefits is not automatic, as organizations must also address managerial and governance challenges associated with AI implementation (Dwivedi et al., 2023; Kostopoulos et al., 2024).

## 1.4 The Growing Importance of AI Governance in Decision-Making

The study indicates that artificial intelligence management is playing a big role in contemporary business research in management, particularly as AI systems become increasingly involved within core organizational decision processes. As organizations rely more heavily on algorithmic insights to support strategic and operational decisions,

governance frameworks are essential to ensure that AI systems operate in a manner that is reliable, accountable, ethically aligned, and strategically coherent. In this context, AI governance can be understood as the set of organizational structures, policies, and oversight mechanisms that guide the development, deployment, monitoring, and evaluation of AI-enabled decision systems (Dwivedi et al., 2023; Wirtz, Weyerer and Sturm, 2023).

The complexity of accountability in managerial decisions supported by AI systems increasing the importance of AI governance. Because algorithmics influence or automate decision process the determination of decision outcomes becomes more difficult. Managers must not only interpret AI-generated insights but also ensure that decisions remain aligned with organizational objectives, ethical standards, and regulatory requirements. Consequently, governance mechanisms play a central role in clarifying accountability structures and establishing human oversight within AI-supported decision architectures (Kostopoulos et al., 2024; Ransbotham et al., 2023).

The research increasingly highlights that effective AI governance requires integration across multiple organizational dimensions, including technical reliability, organizational accountability, and regulatory compliance. From a managerial perspective, governance mechanisms are essential for ensuring data quality, model transparency, risk monitoring, and performance evaluation throughout the AI lifecycle. These mechanisms contribute directly to decision reliability and organizational trust (Soori, Arezoo and Dastres, 2024; De Silva, Halloluwa and Vyas, 2025).

Importantly, empirical evidence suggests that governance capability functions as a mediating factor between technological sophistication and organizational performance outcomes. Organizations with more mature governance frameworks tend to demonstrate higher levels of managerial confidence in AI-supported decisions, improved risk management capability, and stronger stakeholder trust. Conversely, organizations lacking governance maturity face increased implementation uncertainty and greater exposure to ethical and regulatory risks (Dwivedi et al., 2023; Wirtz, Weyerer and Sturm, 2023).

Furthermore, AI governance should be viewed as a dynamic organizational capability rather than a static set of control mechanisms. As AI systems evolve through continuous learning and data accumulation, governance processes must adapt to emerge risks,

technological changes, and strategic opportunities. Organizations that integrate governance into broader strategic processes are more likely to achieve sustainable AI-driven transformation (Ransbotham, S., Kiron, D., LaFountain, B. and Khodabandeh, S. 2023; De Silva, Halloluwa and Vyas, 2025).

Overall, the increasing integration of AI into managerial decision-making highlights the need for governance frameworks that balance performance optimization with ethical responsibility and accountability. Despite growing academic attention, significant gaps remain regarding how organizations operationalize governance mechanisms in real decision environments and how governance structures influence managerial trust and decision effectiveness (Kostopoulos et al., 2024; Soori, Arezoo and Dastres, 2024).

## 1.5 Research Gap

Despite the growing body of literature documenting the performance benefits associated with Artificial Intelligence adoption, significant gaps remain in understanding how organizations operationalize AI governance within real managerial decision environments. Existing research has largely focused on technological capabilities, algorithmic performance, and efficiency outcomes, while comparatively less attention has been given to the organizational and governance conditions that enable effective and responsible AI-supported decision-making (Dwivedi et al., 2023; Wirtz, Weyerer and Sturm, 2023).

In particular, there is a lack of integrated frameworks that simultaneously address decision performance, ethical accountability, and governance maturity. Much of the existing literature treats performance optimization and ethical governance as separate domains, resulting in limited understanding of how organizations balance efficiency gains with transparency, accountability, and regulatory alignment in practice (Kostopoulos et al., 2024; Soori, Arezoo and Dastres, 2024).

Another important gap concerns the role of managerial trust in AI-supported decision processes. While the studies have shown that trust is very important among businesses the empirical research indicates limited effectiveness in decision making influence. Trust appears to be influenced by factors such as system transparency, data quality, explainability, and human oversight mechanisms (De Silva, Halloluwa and Vyas, 2025; Dwivedi et al., 2023).

Furthermore, the practical guidance is limited regarding how organizations can balance automation with human judgment in complex decision contexts. Although the concept of human–AI collaboration is widely discussed, empirical insights into how organizations design hybrid decision architectures that integrate algorithmic insights with managerial oversight remain insufficient (Ransbotham et al., 2023; Wirtz, Weyerer and Sturm, 2023).

These gaps highlight the need for research on how AI can enhance business intelligence not only from a technological point of view, but also by adding value in governance maturity, the managers trust on AI and the improvement of managers and AI collaboration. Regarding these issues is essential for developing practical frameworks that support responsible and effective AI integration in organizational decision-making. The present study responds to this need by combining empirical insights from organizational case studies and semi-structured interviews in order to develop an integrated AI Decision Governance Framework that bridges performance optimization with ethical and governance considerations.

## 1.6 Research Aim and Objectives

The primary aim of this study is to examine the impact of Artificial Intelligence on managerial decision-making process. The focus is exploring the conditions within organizations, that can achieve a more effective, trustworthy and responsible implementation of AI supported decision environments. In particular, the research wants to address how AI adoption can influence the quality on decisions and offer greater confidence to managers working on complex data driven environments. By addressing these dimensions, the study aims to contribute to a deeper understanding of the relationship between technological capability and organizational decision effectiveness.

In order to achieve this, aim the study is interested in several correlated objectives. First, it tries to evaluate how AI implementations affect managerial decision performance, such us decision speed, the accuracy in analysis and the effectiveness of different strategies. Second, the study aims to identify what the challenges are in governance who is associated with AI implementation. The focus is on accountability structures, transparency, and oversight mechanisms that influence decision reliability and

organizational trust. Third, the research explores the role of managers trust in AI-processes that are supported by AI seeking the key factors that shape trust in organizational environments. trust formation and examines the factors that shape. Fourth, the study explores the correlation between humans and AI, emphasizing the balance between algorithmic automation and managerial judgment in hybrid decision environments.

Building on these empirical insights, the final objective of the research is to propose a combined AI Decision Governance Framework that provides practical guidance for organizations seeking to implement AI in a manner that enhances decision performance while maintaining transparency, accountability, and ethical alignment. Through this framework, the study aims to bridge the gap between theoretical understanding and managerial practice in AI in business intelligence.

## 1.7 Research Questions

In the effort of understanding the identified research gaps and the objectives of this study, this research is forming a set of questions that seeks the impact of Artificial Intelligence on managerial decision-making. Also, examining the organizational conditions that enables an effective and responsible AI integration. The purpose is to be examined both the implemented performance and the changes need to be made in governance associated in AI decision making systems.

The study is structured around the following primary research questions:

**RQ1:** How managerial decision-making process are influenced by adopting Artificial Intelligence and how effective could be in business context?

**RQ2:** What opportunities and challenges emerge from AI-supported decision environments in relation to governance, trust, and organizational performance?

**RQ3:** How can organizations design governance structures that enable effective, ethical, and trustworthy integration of Artificial Intelligence into managerial decision-making processes?

To further explore these dimensions and capture the human and organizational factors influencing AI adoption, the study also considers the following sub-questions:

**SQ1:** What are the key factors that influence managerial trust and acceptance of AI-supported decision systems?

**SQ2:** How do organizational needs and managerial expectations shape the integration of Artificial Intelligence into decision-making practices?

Together, these research questions provide a comprehensive framework for investigating the interaction between technological capability, governance maturity, and human decision processes. The findings from these questions support the idea of an intergraded decision governance framework with AI, aiming to enhance decision performance and strengthen responsibility in business intelligence.

## 1.8 Significance of the Study

This study contributes by researching business intelligence in organizations who use AI systems to intergrade theories from decision science, strategic management and AI governance. The existing literature has examined the technological capabilities of AI and its performance implications, but limited attention has been given to the organizational and governance conditions that shape effective and responsible AI-supported decision environments. By exploring the interaction between technological capability, managerial trust, governance maturity, and human–AI collaboration, the present research aims to provide a more holistic understanding of how AI influences managerial decision processes within contemporary organizations.

From a theoretical perspective, the study advances knowledge by bridging fragmented research domains that are often examined separately, including AI adoption, decision effectiveness, and governance mechanisms. The proposed integration contributes to the conceptualization of AI governance as a mediating organizational capability that influences both decision quality and organizational performance outcomes. In doing so, the research extends existing discussions on socio-technical systems and dynamic capabilities by positioning governance maturity as a critical factor in successful AI-enabled transformation.

The practical contribution of the study is the offer of valuable opinions for managers and organizations trying to intergrade AI into the process of decision making in way that enhances the working results while keeping accountability and moral values. As AI plays a big role in strategy and operation decision, the companies facing important

challenges around transparency in how artificial intelligence behaves in work environments. The key factor in reducing implementation risks is to make a solid and transparent AI governance. The study framework aims to support managers balance performance optimization with the requirements of governance. In order to create Value in business creation. Overall, the importance of the dissertation is that addresses a critical and current managerial challenge. The question is how organization can use business intelligence to add value and lower the risk in decision making, who applies in speed and complex markets and what ethical and others limitations AI must address.

## 1.9 Chapter Conclusion

The first chapter introduces the context of the research by examining the accelerating role of Artificial Intelligence in data driven managerial topics associated with decision supporting roles. The dissertation highlights the potential on behavioral perspectives. The predictions related to market reactions may provide valuable foresight by capturing the wisdom of crowds on market participants and their assessments of value creation. As a result, these predictions, whereas probabilistic in nature, can enhance acquisition decision making in areas such as deal selection and target identification. Furthermore, the predictions and the foresight they provide do not shape managerial expectations, and when actual market reactions deviate from predictions, they stimulate additional information gathering, which is reflected in processes such as deal completion. The chapter also identified important research gaps concerning how organizations operationalize governance mechanisms and balance technological capability with accountability and ethical considerations.

As a result, the chapter succeeds the research purpose, objectives, and rises research questions, positioning the study within the broader academic discourse on AI adoption and organizational transformation. The importance of the research was shown by highlighting its help to both theoretical level and practical, through the establishment of an integrated AI Decision Governance Framework.

The following chapter reviews the existing literature on Artificial Intelligence, decision-making, and strategy settings in greater depth in order to establish the theoretical foundations that inform the practical research which will follow in later chapters.

## 2.1 Artificial Intelligence as a Core Driver of Organizational Decision Transformation

Today Artificial intelligence (AI) isn't just a help in order to analyze high forms of technology but became one of the most important pioneers of transformation in big organizations and a great tool of breaking boundaries in the world of information. We have to acknowledge that the last few years, companies have intergraded AI technologies into: how to plan and create strategies to optimize operations, to provide each customer with necessary analytics, to manage supply chain and create the right procedure in order to enterprise risk assessment as needed. This transformation changes data-driven business models at its core, where organizations can rely more heavily on advanced analytics and intelligent systems in order to improve the quality of their decisions and their strategic responsiveness (Soori, Arezoo and Dastres, 2024; Dwivedi et al., 2023).

Due to the speed of machine learning algorithms and predictive analysis the companies can process information and evaluate business opportunities in a more accurate way. Also cloud computing systems have changed the way companies collect, store and analyze information nowadays. Well-known companies use daily cloud-based platforms in order to process big volume of data in a more efficient way and understand what managers need to take the best decisions based to a well-informed ground in real time, relying on clients buying behaviors and cultures.

For example, companies use platforms such as Microsoft Azure and Google Cloud to understand the customers working procedures and ethics, to monitor the performances of their work, to support predictive analytics and create an image for the future. A retail company can use Microsoft Azure to collect sales data from different stores and apply AI models that predict customer demand and stock shortages. Similarly, Google Cloud can help businesses analyze customer behavior and market trends through machine learning tools and real-time data processing.

Artificial Intelligence systems can provide large volumes of data with basic or analytical structures in real time giving managers the tools to identify patterns correlations and trends which couldn't be detected through the classic approach and professional behaviors, allowing organizations to create the right patterns, correlations, and recent trends that may remain undetected through traditional analytical procedures. In highly dynamic and full or risk business environments. These acts can claim faster and more proactive managerial answers, something critical in today's situations where decision speed with high accuracy results are considered critical organizational factors (Ravi et al., 2025; Brynjolfsson, Li and Raymond, 2023).

Recent studies indicates that companies using AI technologies can armor managers and create professionals who take simultaneously decisions by reducing the time is needed in processing data, and separate the analytical performance and business operation. As a

result, organizations strategically move from reactive decision-making approaches toward predictive and prescriptive models that allow minimization of risks and business opportunities (Kostopoulos et al., 2024; Soori, Arezoo and Dastres, 2024). At the same time AI tools improve time efficiency by shifting labor-intensive operation, These acts often consume so much valuable time and expensive resources, making HR professionals' ability and life difficult to engage in higher-order activities such as talent strategy, leadership capabilities, development, and organizational culture in which AI systems can contribute to more continuous high performance monitoring by developing a real-time analytical feedback that supports organizational adaptability and strategic flexibility for greater results.

However, the literature also signs that the effectiveness of AI in managerial decision-making depends not only on sophisticated technology but also on the interaction between AI systems and human ethos. Is commonly known that AI technologies can process data with better speed and analytical depth than a human brain but manager's interpretations remain the foundation of complex organizational environments where ethical concerns, understanding of difficult contexts, stakeholder expectations, and strategic uncertainty influence the final decisions. For this reason, recent research increasingly supports hybrid human-AI decision environments where algorithmic capabilities work hand by hand rather than replace managerial final decisions. (Baird and Maruping, 2021; Pathirannehelage, 2025).

As the evolution of AI is becoming more present into critical decision processes many governance and accountability challenges arise. As algorithmic systems determine the strategic and operational decisions, organizations are required to reconsider traditional authority structures and responsibility boundaries between AI and human authorities. Academic literature increasingly highlights concerns regarding transparency, explainability, accountability, and ethical oversight in AI-supported environments and social working groups (Wirtz, Weyerer and Sturm, 2023; Kostopoulos et al., 2024). In particular, organizations must establish governance laws and mechanisms capable of supervising the entire AI lifecycle, including data quality management, model development, monitoring procedures, and risk control practices. Unless companies create effective governance structures, companies may face trouble in implementing their policies. Also reduced managerial trust, and increased exposure to ethical or regulatory risks.

In addition, the growing dependence on AI technologies affects the roles of managers and the culture of companies in general. Nowadays Managers are expected to evaluate complex algorithmic outputs, oversee AI supported procedures and create a balance between technology recommendations and human judgment. This shift gradually transforms managerial responsibilities and requires new organizational capabilities related to AI literacy, governance maturity, and cross-functional collaboration (De Silva, Halloluwa and Vyas, 2025; Dwivedi et al., 2023).

Overall, the literature shows us that artificial intelligence is changing decision making in companies and organizations by representing the flow of information, the manager's leadership and the structure of decision-making authority. The successful integration of AI therefore requires not only advanced technological tools but also strong governance frameworks, leadership support, and responsible decision practices that maintain accountability and organizational. Understanding this broader organizational transformation provides an important theoretical foundation for examining how AI influences managerial

decision-making effectiveness and governance maturity, which represent central themes of the present study.

## 2.2 Evolution from Automation to Human–AI Collaborative Decision Models

Most of the decision support systems understood technology's impact as a way for automatic acts, a way to improve efficiency and reduce the costs of projects. Traditional decision systems were designed in order to reduce humans working hours and to improve the processing speed through basic procedures and structured data analysis. In many business environments, technology was primarily designed to make auto repetitive energies and standard tasks of operational processes. As a result, technological systems were often viewed as substitutes for human effort, especially in routine and highly structured activities (Simon, 1997; Bostrom and Heinen, 1977).

As Artificial intelligence progressed, the role of AI tools in decision-making changed drastically. Now, collaboration between managers and intelligent systems rather than replacing the human factor is the current procedure. Modern AI-supported systems are increasingly used as tools that will cooperate with managers during decision processes by offering predictive layers, data analysis, and strategic recommendations. AI systems are now viewed as analytical partners that support human in decision making in more complex business environments, rather than excluding the managerial judgment. (Baird and Maruping, 2021; Pathirannehelage, 2025).

Today, companies have induced hybrid decision models where managers and AI systems work together and communicate about the responsibilities across strategies and operations., giving reports to each other during the process. AI can load large amounts of data with an analytical scope, identify patterns, and improve forecasting accuracy, while managers can have a better interpretation and ethical judgment on strategic thinking. Several studies prove that this collaboration between humans and AI can create decisions with great quality and operational performance, particularly in environments characterized by uncertainty and rapid market changes (Pathirannehelage, 2025).

Recent research also identifies different kinds of forms of collaboration between human decision-makers and AI systems. In some business settings, AI technologies mainly provide recommendations that support managerial decisions. In other cases, AI systems can execute predefined actions always under the human supervision of each act. More advanced models involve continuous interaction between managers and AI tools, where decision authority is shared depending on the level of complexity, uncertainty, and business risk involved (Jean and Le Pera, 2025; De Silva, Halloluwa and Vyas, 2025).

In business field is often observed that hybrid AI and human environments often have better results than fully automated or solely human decision logic. The human factor remains important because managers are necessary in evaluating ethical values, stakeholders' expectations and exceptional situations that AI systems cannot fully understand. At the same time, AI technologies will provide with analytical speed, pattern recognition, and data processing capability. This balance between technological support and managerial oversight

is increasingly viewed as a key factor for effective business decision-making balance (Kostopoulos et al., 2024; Ravi et al., 2025).

Moreover, recent studies emphasize that successful human and AI collaboration depends mainly on trust, transparency in process and governance mechanisms. Managers have to understand when they can rely on AI recommendations and when human intervention is required. As a result, businesses are increasingly expected to develop governance practices that support explainability, accountability, and responsible AI use within decision-making processes (Wirtz, Weyerer and Sturm, 2023; Dwivedi et al., 2023).

Overall, the transition from automation-based systems to collaborative human–AI decision models represent an important change in managerial decision-making theory and business practice. AI is no longer viewed only as a tool for replacing human activities, but increasingly as a technology that supports managers in handling more complex and data-intensive business environments. This transition also highlights the growing importance of governance structures, managerial trust, and responsible AI integration, which are central themes of the present study.

## 2.3 Managerial Decision-Making Theory and Cognitive Perspectives

Managerial decision-making theory plays a very important role in management and organizational research. The quick decision-making theory developed by classical economic theory assumed that managers approach decisions as a routine process, in which they collect all the data, evaluate all options in order to maximize utility and finally decide what is best for them and the company they are a part of. However, Hebert Simon later challenged this theory through the theory of bounded rationality in which he said that managers have many limitations related to their time schedule which is filled with pressure, incomplete information, hard and complex data, cognitive capacity and environments that evolve quickly. As a result, they end up taking just satisfying decisions. The Managerial decision-making has remained an important topic in management and organizational research because businesses constantly need to keep up evaluating information, manage uncertainty, and select the right strategic actions. However, later studies demonstrated that real business decisions rarely follow fully rational models because managers often operate under time pressure, incomplete information, and uncertain market conditions (Soori et al., 2024; Ravi et al., 2025). This makes us realize the importance of the boundaries that rationality theory has, which explains that managers make decisions under cognitive and informational limits rather than through fully optimized analytical processes which would give a full circle answer to any problem.

Bounded rationality suggests that decision-makers often are driven to work within limits of time, related to available information, and human cognitive capacity. As a result, managers often rely on simplified and basic answers based on previous experience, and practical judgment in order to reach decisions in complex business environments with decent success. Research indicates that managerial decisions are frequently influenced by heuristics and mental shortcuts, especially in situations characterized by uncertainty and operational pressure (Kostopoulos et al., 2024; Ravi et al., 2025). The heuristics and cognitive biases

theory was mainly developed by Daniel Kahneman and Amos Tversky. Their research challenged the old academic assumption that managers and individuals always make fully rational decision during the problems we mentioned before. According to this theory, decision-makers often rely on heuristics, which are simplified mental shortcuts used to make faster decisions in order to provide an answer even if this answer doesn't give a real closure to a question.

Kahneman and Tversky argued that heuristics help managers process information more quickly in complex business environments. However, these simplified reasoning processes may also lead to cognitive biases and inaccurate judgments. Several common heuristics were identified in their research.

One important example is how available heuristic can be, where managers rely more heavily on information that is recent, quick data or easily remembered. Another example is the anchoring heuristic, where decision-makers become strongly influenced by the first piece of information they receive, such as an initial budget estimate or market forecast. In addition, the representation heuristic occurs when managers assume that a current situation will follow patterns similar to previous experiences without fully evaluating new clues of how the market responds daily.

The theory is particularly important in managerial decision-making because it explains why managers may sometimes make rushed or non-optimal decisions, especially in uncertain and high-pressure business environments. More recent research also suggests that Artificial Intelligence systems can help reduce certain human square logic through data-driven analysis and predictive modelling suggestions. However, businesses may also face new risks related to automation bias, where managers place excessive trust in AI-generated recommendations without sufficient critical evaluation (Kostopoulos et al., 2024; De Silva, Halloluwa and Vyas, 2025).

The healthy perspectives on managerial decision-making also emphasize the importance of intuition, experience, past results and human judgment during strategic processes. Several studies distinguish between analytical reasoning, which is based on structured analysis and data evaluation, and intuitive reasoning, which relies more on past experience, quick interpretation, and pattern understanding. In many business environments, managers combine analytical information with intuition in order to improve decision effectiveness. Nevertheless, research also suggests that intuitive decision-making may increase the possibility of cognitive biases such as overconfidence, confirmation bias, and anchoring effects, which can negatively affect decision quality and organizational performance (De Silva, Halloluwa and Vyas, 2025; Górká et al., 2025).

The increasing adoption of Artificial Intelligence gave us new dimensions into managerial decision-making theories and thesis. AI-supported systems allow businesses to process large volumes of information, identify hidden patterns and clues, generating predictive insights more efficiently than traditional past analytical approaches. In recent years, it has been increasingly observed that businesses use AI technologies not only to automatize operations to tasks but also to support strategic and managerial decisions in more complex business settings (Ravi et al., 2025). From this perspective, AI is viewed more as a tool that strengthens managerial cognition rather than completely replacing human decision-makers (Baird and Maruping, 2021).

A key application of AI-based systems in organizations is for augmenting decision making with AI-generated predictions and insights – a phenomenon referred to as AI-augmented decision making (AIADM). The key role in using AI augmented decision-making tools is that they are capable of processing a big amount of data, which when combined with human judgment and decision making can create significant value for companies. The gradual implementation of AI into managerial processes therefore represents a gradual transition from purely human judgment toward hybrid decision environments where managers and intelligent systems collaborate during analytical and strategic activities. In these environments, AI systems can contribute through the ability of forecast and the pattern recognition power, while managers provide contextual understanding, ethical evaluation, communication skills, and strategic interpretation. Several empirical studies suggest that this balance between human oversight and AI-supported analysis can improve decision performance and operational effectiveness, particularly in uncertain and data-intensive business environments. Also, AI analysis of data demonstrates recent advancements in deep learning architectures, and data analysis. (Pathirannehelage, 2025).

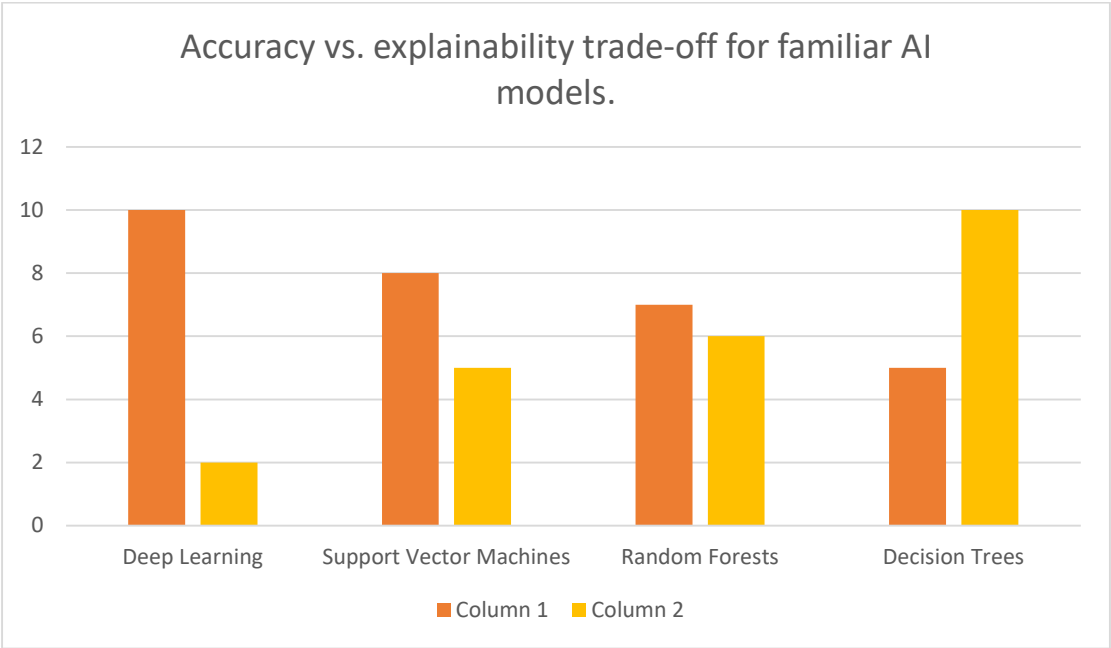
Decision Quality Theory, mainly associated with Ronald Howard, describes decision as an irrevocable allocation of resources because after a taken decision is impossible or very costly to return to the status before the decision was made. Also, it suggests that a decision is not a mental commitment to follow a set of actions but rather the actual pursuit of that course of actions. High-quality decisions follow some steps. At first, we should identify what decision we have to take and what are the alternatives. Then we have to gather the proper information, determine dominance and sensitivity analysis and afterwards we proceed to the probabilistic phase in which we encode uncertainty and risk performance and finally we select the best decision. AI can contribute a lot in probabilistic and reasoning phase because it can code better uncertainty, make simulations of the alternatives and estimate valuable probabilities. AI technologies can improve several of these dimensions by reducing the time required for data analysis, increasing forecasting accuracy, and supporting scenario modelling in complex environments (Ravi et al., 2025; Górká et al., 2025).



However, decision quality also depends on factors such as ethical awareness, stakeholder understanding, and contextual interpretation, where human judgment remains particularly important. Research additionally highlights that decision effectiveness is influenced not only by individual cognitive processes but also by broader organizational conditions. Leadership style, communication structures, governance mechanisms, and company's culture affect how managers interpret information and apply decisions within businesses. As companies increasingly adopt AI-supported systems, managerial roles are gradually changing toward

supervising analytical outputs, evaluating system reliability, and balancing algorithmic recommendations with business priorities and ethical considerations (Dwivedi et al., 2023; Wirtz, Weyerer and Sturm, 2023).

At the same time, the integration of AI into managerial decision-making creates additional risks associated with automation bias and excessive dependence on algorithmic outputs. Many AI methods are using complex Machine Learning (ML) algorithms (e.g., Deep Neural Networks) for solving a wide range of tasks. The problem is that the most effective algorithms lack in results trust and explainability because they operate as black boxes because the most effective models in terms of accuracy are the least explainable and vice versa. So, there is a dilemma between accuracy and explainability. Many new methods trying to deal with this problem, for example Artificial Intelligence (XAI) methods. XAI is a sub-field of AI which provides the appropriate methodologies for explaining and interpreting the results produced by complicated ML models (Kostopoulos, Davrazos and Kotsiantis, 2024).



Source: Author’s own elaboration based on Kostopoulos, Davrazos and Kotsiantis (2024).

Managers may place too much trust in AI-generated recommendations without sufficient critical evaluation, especially when systems appear highly accurate. On the other hand, low trust in AI systems may reduce the effective use of technological capabilities. For this reason, recent studies emphasize that businesses need to maintain a balanced relationship between managerial judgment and AI-supported analysis in order to achieve more reliable and responsible decision outcomes (Kostopoulos et al., 2024; De Silva, Halloluwa and Vyas, 2025).

Overall, the theories of managerial decision making provide an important theoretical foundation for understanding how decisions in business environments are affected by AI tools. The interaction between the human cognition and the capabilities of technology within organizations structure can create highly complex decision processes where both analytical performance and managerial interpretation influence organizational outcomes. This perspective supports the broader argument of the present study that AI adoption

should be examined not only as a technological development but also as a transformation of managerial decision-making practices and governance processes.

## 2.4 Opportunities of AI in Managerial Decision-Making

Most of the breakthrough and advanced opportunities have been given through academic research associated with managerial decision intergraded with Artificial intelligence into business operations. As businesses increasingly act in data-intensive and highly competitive environments, AI technologies can offer faster info analysis, predictive insights, and more effective strategic responses. All these capabilities and tools can help companies not only improve operational performance but also to help them have a better respond to all market changes and challenges business face. (Ravi et al., 2025; Górka et al., 2025).

One of the most important advantages of AI implementation is the improvement of speed in decisions and the efficiency in analysis process. With AI supported systems business can process large amount of data in real time faster than traditional analysis style. These actions are very important in industries where the rapid decisions can affect the performance in operations and offer a competitive advantage between competitors. By reducing the time required for information processing and analysis, AI systems help managers focus more on strategic interpretation and implementation rather than manual analytical tasks (Soori, Arezoo and Dastres, 2024).

For instance, businesses that use platforms such as Microsoft Azure or Google Cloud have the ability to process big volumes of customer behavioral data and operational data in real time as a problem rises. AI managers can detect rising market trends, monitor how their business performs and make faster decisions in their strategy without further hesitation. For example, in the banking sector, AI tools have been using more and more skills that evaluate customers credit scores in order to support loan approval procedures or detect fraud transactions through machine learning models that analyze in a more quick and efficient way than traditional customers evaluation models. (Papagiannidis et al., 2025; Wirtz et al., 2023; Lahusen et al., 2024). More recent studies also suggest that AI-supported credit scoring systems improve forecasting accuracy and help banks reduce operational risk while supporting more reliable lending decisions knowing not only the future procedures but their clients background as well (Pathirannehelage, 2025; De Silva et al., 2025).

Another important opportunity created by AI is the improvement of forecasting capability and predictive accuracy. Machine learning systems can identify emerging patterns, detect operational anomalies, and predict potential risks earlier than many traditional analytical methods. A most accurate forecast supports better allocation in resources related to planning in strategic investments for now and for the future. Also, more efficient decisions in risk management can be taken from managers within businesses. The predictive analysis also can offer managers a better evaluation in different business scenarios so they can estimate more accurate the different outcomes in many scenarios into business. This capability supports a more proactive approach to managerial decision-making rather than relying only on reactive responses to business problems (Ravi et al., 2025; Kostopoulos et al., 2024).

In the maritime industry these kinds of developments have been made. Shipping companies increasingly use AI systems in order to improve routes, fuel stock, predict the needs for maintenance and operational monitoring. AI-supported analytics allow maritime businesses to process environmental and operational data in real time in order to improve safety, reduce operational costs, and support faster decision-making during shipping activities (Soori et al. 2024; Papagiannidis et al. 2025).

In addition, predictive AI systems help shipping companies identify possible operational disruptions earlier and improve logistics coordination across ports and supply chain networks (Dwivedi et al. 2023; Lahusen et al. 2024).

AI technologies can also give innovative solutions and ideas across organizations and more flexible strategies. AI systems also are used, not only to analyze customer behaviors but also to evaluate market trends, and make simulations in different business strategies before they implement it giving its final opinion into a task. These processes help firms reduce experimentation costs, improve quick learning capability, and accelerate innovation activities. Recent studies indicate that businesses integrating AI into decision-making processes often demonstrate higher adaptability and stronger responsiveness to environmental and market changes (Dwivedi et al., 2023; Górka et al., 2025).

Another important advantage of AI adoption is continuous performance monitoring across business operations without losing a single beat. Real-time analytics and AI-supported monitoring systems allow managers to identify deviations from expected performance levels and respond more quickly to operational problems. This continuous analytical feedback supports organizational learning, improves operational control, and contributes to better decision accuracy in complex business environments (De Silva et al. (2025)).

At the same time, the literature increasingly emphasizes that the benefits of AI are greater when technological capabilities are combined with human managerial strengths. AI systems improve analytical speed and pattern recognition, while managers contribute contextual understanding, communication skills, ethical judgment, and strategic interpretation. Several studies suggest that this collaboration between managers and AI systems can improve innovation performance, operational coordination, and governance effectiveness within businesses (De Silva, Halloluwa and Vyas, 2025).

More recent research also highlights that responsible AI governance practices positively influence organizational performance. Businesses that develop stronger command mechanisms related to transparency, accountability, and explainability often achieve higher managerial trust and more effective integration of AI technologies into strategic decision-making processes (Wirtz, Weyerer and Sturm, 2023; Kostopoulos et al., 2024). These findings support the view and the idea that AI should not be seen only as a tool for improving efficiency, but also as an important strategic capability that supports long-term business development and decision effectiveness.

Overall, the opportunities in a world associated with AI adoption can demonstrate its potential to improve managerial decision-making and business performance across different industries, countries and help managers with different cultures as well. However, the successful realization of these benefits also depends on how businesses address challenges related to governance, trust, transparency, and responsible AI implementation, which are examined in the following section.

## 2.5 Challenges and Risks of AI-Driven Decision Environments

Artificial Intelligence is offering many important advantages for managers in decision-making. Although the literature identifies several challenges in management, organization policies and in ethical perception. All that are affecting a proper integration of AI into business environments. The most recent studies suggest that technological improvements alone are not enough to ensure a successful AI adoption. Instead, the effectiveness of AI implementation depends on the interaction between technology, governance practices, organizational readiness, and managerial trust (De Silva, Halloluwa and Vyas, 2025; Ravi et al., 2025).

Transparency and explainability are some of the most frequently discussed challenges related to AI supported systems. The most advanced AI models have highly complex processes in analysis, so managers may find it difficult to fully understand or interpret how the outcome was generated. When managers have to explain or justify strategic decisions and explain how particular outcome were produced in projects, they facing great difficulties in analyzing it. However, “black box” AI systems often reduce visibility into the analytical logic of algorithms, creating concerns related to accountability, responsibility, and managerial trust (Kostopoulos et al., 2024). As a result, explainable Artificial Intelligence has become an increasingly important research area that focuses on improving transparency, interpretability, and trust in AI-supported decision systems.

Also, algorithmic bias and fairness related to AI algorithms is another important challenge. Because AI systems are trained on using historical datasets, they may unintentionally reproduce existing inequalities, jump in inaccurate assumptions or making biased decisions, which are already embedded within organizational data. In the banking sector, recruitment, healthcare, and insurance, biased AI-supported decisions may create ethical concerns or reputational damage. Also, businesses may face many legal risks. For instance, when a bank has to evaluate customer’s creditworthiness, the AI scoring systems, may use historical financial data which already reflect social or economic inequalities. As a result, some customer groups may be unfairly disadvantaged during loan approval procedures (Papagiannidis et al., 2025; Wirtz et al., 2023; Lahusen et al., 2024).

This overdependence may reduce independent Managers judgment and weaken important cognitive skills related to analytical thinking, data interpretation, and strategic evaluation. As businesses increasingly automate analytical tasks, there is growing concern that some managers may lose part of their ability to critically process information and challenge algorithmic recommendations effectively (Ravi et al., 2025). For this reason, several studies emphasize that businesses should maintain strong human oversight and balanced collaboration between managers and AI systems.

Research additionally identifies strong concerns related to privacy matters, cybersecurity and protection of data. AI systems can often use cloud-based technologies and digital infrastructures to process large volumes of sensitive financial and operational information. If a business has weak cybersecurity practices or poor data governance, may be exposed to cyberattacks, violations in privacy and disruptions in operations. In industries such as banking

and maritime transportation, where real-time operational data is critical, failures in data protection may significantly affect operational continuity and stakeholder trust (Soori et al. 2024; Papagiannidis et al. 2025).

Another growing ethical issue relates to the use of deepfake technologies and AI-generated misinformation. Recent developments in generative AI can allow the creation of highly realistic fake videos, voice recordings, and digital content that can manipulate public opinion. Misinformation can damage reputations and reduce trust in digital communication environments. Businesses increasingly face risks associated with manipulation of identity or campaigns aiming to mislead the public opinion with fake AI-generated content. All the above are creating additional governance and security challenges for companies operating in digital environments (Dwivedi et al. 2023; Lahusen et al. 2024).

In addition to ethical and technical concerns also organizational barriers can represent a major challenge for successful AI adoption. Many employers' showing resistance because they are not well trained and have a limited AI literacy or a lack of specialized skills. These cultural resistance to technological change may frequently reduce the effective use of AI systems in business environments. Some managers may hesitate to rely on AI-generated insights because of concerns related to reliability or they are afraid of reduced managerial control. Some managers also fear that technology may gradually replace professional expertise. These findings suggest that AI adoption challenges are often organizational and behavioral rather than purely technological, reinforcing the importance De Silva et al. (2025); De Silva, Halloluwa and Vyas, 2025).

Overall, the regulations alignment is required in order to achieve more effective and responsible AI adoption. These challenges further highlight the growing importance of structured AI governance frameworks capable of supporting trustworthy and sustainable managerial decision-making processes, which are examined in the following section.

## 2.6 The Role of Trust, Transparency, and Leadership in Human–AI Decision Systems

One of the most important factors that influencing a successful adoption of AI in decision-making environments is trust. While Human-Centered AI (HCAI) aligns more with human values Explainable AI (XAI) enhance more transparency because they present decisions in a more understanding way. However, AI is less effective in critical decision-making scenarios. Recent studies suggest that trust affects how managers use AI systems, how much they rely on AI-generated recommendations, and how effective collaboration between humans and AI becomes in practice (Ravi et al., 2025; De Silva, Halloluwa and Vyas, 2025). Despite the big progress of HCAI and (XAI) independently the collaboration of the systems is a project in progress. Agile software development provides a practical context to explore this integration due to its explicit emphasis on human factors, adaptability, and iterative responsiveness to change (Silva, Halloluwa and Vyas, 2025). By enhancing AI systems with more human factors derived from psychology, such as the human response to change, we can increase human trust in AI systems. The key principle of HCAI is augmentation over automation. The AI systems should support managers' decision rather than fully automate their tasks. The second key factor is that users should have the control and the ability to make modifications

to AI behavior depending on their needs. The third key factor is AI systems should be designed in order to minimize bias and ensure fair outcomes and at last AI should enable seamless collaboration between humans and AI technology (Silva, Halloluwa and Vyas, 2025). The XAI refers to methods that explain AI decision making process understandable to humans. The power to explain how the AI data are generated increases the trust, accountability, and compliance with ethical and regulatory standards (Ravi et al., 2025; De Silva, Halloluwa and Vyas, 2025).

### *Core Aspects of XAI*

#### Interpretable Models

- should be inherently understandable or provide post hoc explanations

#### Users - Centric Explanations

- explanations should be adapted to users' expertise and needs

#### Transparency and Accountability

- AI systems should reveal their decision making logic to users

#### Evaluation and Explanations

- methods should be provided to assess the effectiveness of AI explanations in fostering trust and usability

*Source: Author's own elaboration based on Silva, Halloluwa and Vyas (2025).*

In building trust transparency plays a key role. When systems generate outputs or recommendations that can be easily understood by managers is more likely to rely on AI systems. (Kostopoulos et al., 2024).

To bridge the gap of XAI and HCAI we should elaborate on development of AI explanations. The first important dimension is Adaptability. The AI should be offering personalized explanations by utilizing users' profile and promote users' interaction with interactive questions. Also, should be able to combine textual, visual and users' explanations for a better cohesion. The second dimension is context aware transparency in more high-risk fields, for instance in finance more comprehensive explanations should be offered compared to low risk fields. The third dimension is explainability with privacy and security. The AI systems should be transparent but not at the cost of privacy and security by sharing sensitive information. The fourth dimension is how we can measure the impact of explanations in users' trust and the last dimension is ensuring AI systems adhere to global governance standards, because it is critical for accountability and fairness (Silva, Halloluwa and Vyas, 2025).

Leadership additionally plays an important role in shaping trust between managers and AI systems. Organizational leaders influence how AI technologies are introduced and integrated into business processes. Effective leadership helps businesses balance technological

efficiency with ethical oversight and managerial judgment. Leaders also support organizational cultures that encourage responsible AI use, innovation, and continuous learning. Without leadership support, businesses may face resistance, uncertainty, and lower adoption of AI technologies (De Silva et al. (2025)).

Recent research further indicates that human judgment remains necessary in situations involving ethical uncertainty, reputational risks, and complex stakeholder issues. Although AI systems can process information quickly and support analytical tasks, managers still play an important role in interpreting results and evaluating broader business and ethical implications. In many cases, managerial intuition functions as an additional evaluation layer that helps businesses make more balanced and responsible decisions (De Silva, Halloluwa and Vyas, 2025; Pathirannehelage, 2025).

Another important issue affecting trust relates to the reliability of AI-generated outputs. Recent studies identify risks associated with inaccurate or fabricated information generated by advanced AI systems, often described as “hallucinations.” These incorrect outputs may reduce managerial confidence and increase decision-related risks, especially when managers rely heavily on AI recommendations without sufficient critical evaluation. For this reason, businesses increasingly need human oversight and validation procedures in order to maintain reliable decision-making processes (Dwivedi et al. 2023; Ravi et al., 2025).

Overall, trust, transparency, and leadership strongly influence how businesses integrate AI into managerial decision-making processes. The literature suggests that successful human–AI collaboration depends not only on reliable technology but also on governance structures, managerial oversight, and organizational cultures that support responsible AI use. Understanding these factors is important for examining how businesses can develop trustworthy and effective AI-supported decision environments.

## 2.7 Socio-Technical Perspective on AI Adoption

The adoption of Artificial Intelligence in businesses should not be viewed only as a technological implementation process. Recent literature increasingly suggests that AI adoption represents a broader socio-technical transformation involving technology, managers, employees, organizational culture, and governance structures. Socio-technical systems theory explains that organizational performance depends on the interaction between technological capabilities and social factors such as leadership, communication, organizational culture, and employee skills (De Silva, Halloluwa and Vyas, 2025; Ravi et al., 2025).

From this perspective, successful AI integration depends not only on technological performance but also on how businesses adapt their processes, managerial roles, and decision structures to new technological environments. In many cases, businesses with advanced AI technologies still face implementation difficulties because organizational processes and employee capabilities are not fully aligned with technological change (De Silva et al. (2025)).

At the human level, AI adoption requires managers and employees to develop new competencies related to data literacy, analytical interpretation, and collaboration with AI-supported systems. In several business environments, employees may feel uncertain about

the growing role of AI technologies or fear that automation may reduce professional autonomy and job security. Managers may also hesitate to rely on AI-generated recommendations because of concerns related to reliability, accountability, and loss of control over decision processes (De Silva, Halloluwa and Vyas, 2025; Pathirannehelage, 2025).

Research further suggests that organizational and behavioral factors can enhance the resistance in AI adoption rather than technical limitations alone. For this reason, in order to achieve a successful AI integration, the changes have to be approved by the leaders and train properly the employers. Also, the leadership has to communicate the AI strategies and proceed the changes in management taken under consideration both technical and human concerns (De Silva et al. (2025)).

The Leadership plays an important role for aligning the technological and social dimensions of AI adoption. Because organizational leaders can influence strategic priorities, allocate the resources, and support organizational cultures that encourage innovation and experimentation. In addition, leaders can help businesses establish governance frameworks that define managers accountability and set ethical standards. Also, managerial responsibilities in AI-supported decision environments are very important. Without strong leadership support, businesses may struggle to achieve the expected benefits of AI adoption despite having advanced technological systems (Ravi et al., 2025; Kostopoulos et al. 2024).

The socio-technical perspective is also very important for governance maturity in successful AI integration. Governance mechanisms may help businesses align technological systems with the organizational objectives and optimize risk management practices, and ethical standards. Businesses with stronger governance structures are often better prepared to manage the uncertainty and support transparency. That behavior can maintain trust in AI-supported decision processes. In contrast, weak governance practices may create implementation problems. (Wirtz, Weyerer and Sturm, 2023; Kostopoulos et al., 2024).

Another important issue is that when a business adopts AI creates new forms of collaboration between managers and technological systems. As businesses increasingly rely on AI-supported analytics, managerial roles gradually shift from direct decision execution to a supervisor role who interpretate and oversees the activities. Managers increasingly are functioning as coordinators of human–AI collaboration rather than sole decision-makers. This reflects the growing transition toward augmented intelligence models where human judgment and AI capabilities operate together during strategic and operational decision-making processes (Ravi et al., 2025).

An important framework is given from the socio technical point of view, in order to understand the complexity of AI adoption in modern business environments. Understanding these interactions is important for examining how businesses can develop more effective, trustworthy, and sustainable AI-supported decision environments, which represents a central focus of the present research.

## 2.8 AI Governance and Responsible AI Frameworks

Artificial Intelligence governance has become one of the most important topics in recent management and technology research because businesses increasingly use AI systems in

strategic and operational decision-making processes. AI governance refers to the policies, rules, procedures, and control mechanisms that businesses use in order to manage AI systems responsibly and reduce risks related to transparency, fairness, accountability, and security (De Silva, Halloluwa and Vyas, 2025; Ravi et al., 2025).

Recent studies suggest that businesses cannot rely only on technological performance when adopting AI systems. Instead, organizations need governance frameworks that ensure AI technologies operate in a reliable, ethical, and transparent way throughout their entire lifecycle. Effective AI governance usually includes human oversight procedures, risk management mechanisms, accountability structures, cybersecurity practices, and continuous monitoring processes (Kostopoulos et al., 2024).

More recent governance models increasingly adopt flexible and multi-layered approaches that combine centralized governance standards with decentralized implementation across business units. This allows businesses to maintain consistent governance principles while adapting AI practices to different operational environments and regulatory requirements. Such flexibility is particularly important for multinational companies operating across different legal and institutional systems (Ravi et al., 2025).

The external regulatory environment also plays an increasingly important role in AI governance. Regulatory initiatives such as the European Union Artificial Intelligence Act introduced risk-based governance approaches that require businesses to apply stronger controls to high-risk AI systems. These regulations increase expectations regarding transparency, accountability, explainability, and data protection in AI-supported decision environments. As a result, compliance with AI regulations is increasingly viewed not only as a legal requirement but also as an important strategic factor affecting organizational reputation and long-term competitiveness (Kostopoulos et al., 2024; Dwivedi et al. 2023).

Recent literature additionally highlights the growing complexity of governing advanced generative AI systems. Technologies capable of producing AI-generated text, images, videos, and predictive outputs create new risks related to misinformation, deepfakes, fabricated information, and reduced transparency. These developments reinforce the need for continuous auditing, monitoring, and updating of AI systems throughout their operational lifecycle (Lahusen et al. 2024; Dwivedi et al. 2023).

The concept of governance maturity has also become increasingly important in recent AI research. Governance maturity refers to the ability of businesses to develop structured governance practices that effectively align AI systems with organizational strategy, ethical principles, operational objectives, and risk management processes. Businesses with more mature governance structures are often better prepared to manage uncertainty, maintain managerial trust, and achieve more reliable AI-supported decision outcomes (Ravi et al., 2025; Kostopoulos et al. 2024).

Overall, the literature suggests that governance maturity plays an important role in determining the long-term success of AI adoption in business environments. Businesses that establish effective governance frameworks are more likely to improve transparency, strengthen stakeholder trust, reduce operational risks, and support more responsible AI integration. Understanding the relationship between governance capability, technological performance, and managerial decision effectiveness provides an important foundation for the conceptual framework developed in the present research.

## 2.9 Research Gap and Conceptual Positioning of the Study

The existing body of literature provides substantial insight into the technological capabilities of Artificial Intelligence and its potential to enhance organizational decision-making performance. First, much of the existing literature addresses performance optimization and ethical considerations as separate domains rather than as interconnected dimensions of organizational decision systems. While studies explore efficiency gains, predictive accuracy, and automation benefits, governance research often focuses on ethical compliance and regulatory oversight without fully integrating these perspectives into a unified managerial decision framework. Consequently, there is limited theoretical and practical guidance on how organizations can simultaneously achieve decision performance improvements while maintaining transparency, accountability, and ethical alignment.

## 2.10 Chapter Summary

This chapter reviewed the existing literature on Artificial Intelligence and its role in managerial decision-making within modern business environments. The discussion examined how AI evolved from automation-focused systems toward more collaborative human–AI decision models. The chapter also has explored the opportunities associated with AI adoption. Such as a faster decision-making, an improved forecasting capability and creating more efficient operations and a better ability to adapt in a changing environment.

The chapter also examined some important theoretical perspectives related to how managers making strategic decisions based on AI tools. Particular importance was given to bounded rationality theory, heuristics and cognitive bias theory, decision quality theory and sociotechnical systems theory. These perspectives are helping to be explained how the human cognition, the way that managers decide and organize their procedures and the structure of the organization within complex environments is evolved with AI tools.

The chapter also identified several important research gaps in the current literature. Existing studies still provide limited practical guidance regarding how businesses can balance automation with managerial judgment, develop trustworthy AI governance structures, and integrate decision performance with governance maturity and managerial trust within real organizational environments.

Overall, the literature reviewed in this chapter provides the theoretical foundation for the empirical investigation presented in the following chapter. The next chapter explains the research methodology used in this study in order to examine how businesses implement AI-supported decision systems and how governance structures influence managerial decision effectiveness in practice.

## 3.1 Research Philosophy

The study is based in a realistic research philosophy. The most relevant enterprises are focused in pragmatic management because it is focused on solving real world problems and can create practical procedures and solutions in problems referring in decision making. They do not focus on a sole philosophical perspective and select the most suitable methods for the research. (Saunders, Lewis and Thornhill, 2023).

A key role in intergrading AI in all business's decision making, is pragmatism, because the hardest part in interdependent environments is from conceptualization to create a solid procedure who can be evaluated and finally optimized. Because AI adoption is influenced by multiple dimensions that can connect technology and managerial judgment, the pragmatism philosophy is appropriate for this study. Also, AI integration is requiring an organizational culture, creating governance practices and making new regulations. Understanding these interactions requires a flexible research perspective that can examine both technical and human factors. While efficiency can be achieved by using AI in decision making, human intervention is crucial for monitoring and filter the process. (Ravi et al., 2025; De Silva, Halloluwa and Vyas, 2025).

When managers decisions are supported by AI can evaluate objective and subjective elements and make more accurate predictions because they review data and environment factors with higher accuracy. At the same time, the managers can give a better interpretation on AI outputs by evaluating business implications the priorities of the business and by evaluating the overall context. As a result, AI adoption cannot be fully understood through purely quantitative or purely qualitative perspectives. A pragmatist approach supports the examination of these complex interactions and allows the researcher to focus on practical organizational outcomes (Pathirannehelage, 2025).

Another reason for selecting pragmatism is that this study aims to contribute both to academic knowledge and managerial practice. The research does not only examine the relationship between AI adoption and managerial decision-making but also seeks to develop an AI Decision Governance Framework that can support businesses in real organizational environments. Pragmatism is particularly suitable for applied research because it emphasizes useful findings, practical recommendations, and problem-solving approaches that can be implemented in practice (Saunders, Lewis and Thornhill, 2023).

Finally, pragmatism can support methodological update, which is important for the present study. The research combines evidence from managerial interviews and organizational case studies in order to develop a deeper understanding of AI-supported decision processes. This flexibility allows the researcher to examine governance mechanisms, trust, and managerial judgment from different perspectives and provides a richer understanding of how businesses integrate AI into decision-making activities (Creswell and Creswell, 2023; Ravi et al., 2025).

## 3.2 Research Design and Approach

This study is designed in a qualitative dominant mixed-methods research design. The selected approach combines the qualitative data which collected through managerial interviews with evidence derived from organizational case studies and secondary sources. Mixed-methods research are more appropriate when a research problem requires both in-depth exploration and the examination of evidence from different sources (Creswell and Creswell, 2023; Saunders, Lewis and Thornhill, 2023).

The study follows an exploratory research approach because it seeks to develop a better understanding of how Artificial Intelligence is used in managerial decision-making processes. Particular importance is given to how managers interact with AI-supported systems. Also very important is how trust in AI technologies can develop and used in governance practices within organizations. Since AI adoption continues to evolve rapidly across industries, an exploratory design allows the researcher to investigate emerging practices, challenges, and managerial experiences that may not yet be fully addressed in existing research (Ravi et al., 2025).

The qualitative component of the study provides detailed insights into managerial experiences and perceptions regarding AI adoption. It also helps examine how managers are evaluating AI-generated recommendations and can address potential risks by applying governance mechanisms in everyday decision-making activities. In addition, qualitative research is particularly useful for exploring issues such as trust, human oversight, accountability, and ethical concerns that are difficult to capture through numerical data alone (Creswell and Creswell, 2023).

At the same time, the use of organizational case studies supports the comparison of AI adoption practices in different business environments. This allows the study to identify common patterns as well as differences in how businesses implement AI-supported decision systems. By Comparison in multiple organizational contexts the researcher has better understanding on how factors such as governance maturity, managerial trust, and organizational characteristics influence AI adoption outcomes (Yin, 2024; Pathirannehelage, 2025).

Overall, the selected research design supports the objectives of the study by combining managerial insights with organizational evidence. This approach provides a broader understanding of how AI-supported decision-making operates in practice and how governance mechanisms influence decision effectiveness in different business settings.

## 3.3 Data Collection Methods

### 3.3.1 Primary Data Collection — Semi-Structured Interviews

Primary data were collected through five semi-structured interviews with professionals who had direct experience with AI-supported decision-making processes in their organizations. The participants represented different professional backgrounds, including operations management, business analysis, risk management, compliance, and data analytics. This diversity was considered important because it enabled the collection of different perspectives on AI adoption, governance practices, managerial trust, and decision-making processes.

Semi-structured interviews were selected because they provide a balance between consistency and flexibility. A common set of interview questions ensured that all participants addressed the main themes of the study and the flexible nature of the interviews allowed participants to discuss experiences and challenges specific to their professional roles. This approach is widely used in management research when the objective is to explore perceptions, experiences, and organizational practices in depth (Saunders, Lewis and Thornhill, 2023).

The interview questions were developed directly from the research objectives and research questions presented in Chapter 1. Particular attention was given to issues related to decision performance, trust in AI systems, governance mechanisms, human and AI collaboration, and the challenges associated with AI adoption. The interview protocol therefore focused on understanding how AI is used in organizational decision making and the benefits and risks perceived by managers. Also examined the factors that influence responsible AI implementation.

The use of semi-structured interviews was particularly appropriate because AI adoption differs across organizations, industries, and decision contexts. Participants were therefore encouraged to provide practical examples from their own professional environments. These examples offered valuable insights into how AI technologies support decision-making activities, how governance mechanisms are applied in practice, and how managers can balance AI generated recommendations with the human judgment.

The interviews also provided insights for challenges associated with AI adoption. Participants discussed issues related to transparency the explainability the quality of, the training of the employee and the risk of inaccurate outputs generated by AI systems. Several participants emphasized that trust in AI is developing gradually and influencing by governance structures, system reliability, and opportunities for human oversight. These insights contributed to a richer understanding of the organizational factors that influence AI-supported decision-making.

Overall, the semi structured interviews provided a detailed and context specific evidence that supported the objectives of the study. The method allowed participants to share

practical experiences while enabling the researcher to explore the relationships between AI adoption, governance maturity, managerial trust, and decision effectiveness across different organizational settings.

### 3.3.2 Interview Guide Structure

The interviews were developed based on the research objectives and research questions presented in Chapter 1, as well as the key themes identified in the literature review. The objective was to explore how Artificial Intelligence influences managerial decision making and to examine the organizational factors that support effective and responsible AI adoption.

The interview guide was organized around four thematic areas: decision performance, trust and explainability, governance and risk management, and human–AI collaboration. These themes were selected because they observed consistently throughout the literature review and were closely aligned with the study's conceptual framework. The structure also reflected the main analytical themes that were later explored during the coding process and data analysis.

A total of twelve semi-structured interview questions were developed. The questions examined how AI is used in organizational decision-making, the benefits and challenges associated with AI adoption, the factors influencing managerial trust, the role of governance mechanisms, and the balance between AI-generated recommendations and managerial judgment. Additional attention was given to issues such as transparency, explainability, employee training, data quality, and the risks associated with inaccurate AI outputs.

Although a common interview structure was used across all participants, the interviews remained flexible. Participants were encouraged to discuss examples from their own professional experience and to elaborate on issues they considered important. This flexibility allowed the researcher to explore emerging topics while maintaining consistency with the research objectives and interview protocol.

The semi-structured format was particularly suitable because AI adoption varies across industries, organizational structures, and decision contexts. Allowing participants to provide context related examples generated richer qualitative evidence and contributed to a deeper understanding of how AI-supported decision making operates in practice.

Overall, the interview guide functioned as a structured discussion framework rather than a fixed questionnaire. This approach ensured consistency across interviews while allowing participants to provide detailed insights regarding AI adoption, governance practices, trust formation, and managerial decision-making. The information collected through this process formed the basis for the thematic coding and analysis presented in Chapter 4.

### 3.3.3 Case Study Selection and Secondary Data Sources

In addition to the primary data collected through semi-structured interviews, this study incorporates organizational case studies to examine how Artificial Intelligence is applied in real business environments. The case studies provide practical examples of AI-supported decision making and complement the interview findings by illustrating how organizations address issues related to performance, governance, trust, and human oversight.

Three case studies were selected for the research. The selection was based on purposive criteria and aimed to capture different dimensions of AI adoption. The cases include examples of successful AI implementation, governance challenges, and situations where the use of AI generated ethical concerns or public debate. This approach allowed the study to examine AI adoption from multiple perspectives and to compare different organizational experiences.

The selected cases represent different industries and decision contexts. As a result, they provide useful evidence regarding how organizations implement AI systems, how decision authority is distributed between humans and algorithms, and how governance mechanisms influence decision outcomes. Examining different organizational settings also supported the identification of recurring patterns as well as important contextual differences.

The case studies were developed using secondary data sources. These included academic journal articles, industry reports, publicly available organizational documents, regulatory publications, and other credible sources. The use of secondary data was considered appropriate because extensive documentation already exists regarding the selected cases and their AI-related practices. This allowed the researcher to examine implementation processes, governance approaches, and organizational outcomes without requiring direct access to the organizations involved.

The role of the case studies was primarily analytical rather than descriptive. The cases were used to compare findings from the interviews and to explore how governance mechanisms, trust, and human–AI collaboration influence managerial decision-making in practice. By combining interview evidence with case-based analysis, the study achieved methodological triangulation and developed a broader understanding of AI-supported decision environments.

## 3.4 Sampling Strategy

This study employed purposive sampling to select participants with direct professional experience in AI-supported decision-making processes. The objective of this sampling approach was to obtain informed perspectives from professionals who regularly interact with AI systems and are involved in organizational decision-making activities. The research focused on participants who are experienced and active in business field.

These sampling is widely used in qualitative research when the goal is to gain detailed insights from individuals who possess specific knowledge related to the research topic

(Saunders, Lewis and Thornhill, 2023). In the context of this study, participants were selected based on their familiarity with AI-supported decision environments and their ability to provide practical insights regarding decision performance, governance practices, managerial trust, and human–AI collaboration.

The final sample consisted of five professionals from different organizational functions and industries. The participants represented a range of roles associated with AI adoption and decision-making activities, including operations management, business analysis, risk management, compliance, and data analytics. This diversity enabled the collection of multiple perspectives while maintaining a clear focus on managerial decision processes.

**INTERVIEW PARTICIPANTS PROFILE**

| PARTICIPANT | WORK POSITION      | INDUSTRY           | EXPERIENCE |
|-------------|--------------------|--------------------|------------|
| 1           | Operations Manager | Retail             | 20 years   |
| 2           | Business Analyst   | Technology         | 10 years   |
| 3           | Risk Manager       | Banking            | 15 years   |
| 4           | Compliance Officer | Financial Services | 8 years    |
| 5           | Data Analyst       | Technology         | 5 years    |

As shown in Table above, the participants possessed substantial professional experience and represented different organizational perspectives. This variation supported the exploration of common themes as well as context-specific differences in AI adoption, governance practices, and managerial decision-making.

Although the sample size was limited, it was considered appropriate for the qualitative and exploratory objectives of the study. The focus of the research was to obtain in-depth insights rather than achieve statistical generalization. The selected participants provided sufficient diversity and expertise to support the thematic analysis and address the research questions.

Overall, the purposive sampling strategy aligned with the qualitative design of the study and facilitated the collection of rich empirical evidence regarding AI-supported decision-making within contemporary organizational environments.

### 3.5 Research Strategy Justification

This study has adopted combined semi structured interviews on the job business analysis in order to examine Artificial Intelligence adoption within managerial decision-making environments. This approach was selected because of the complex phenomenon involving technological capabilities, managerial judgment, governance mechanisms, and human behavior. Understanding these interactions requires methods capable of capturing both organizational context and managerial experience.

Mainly for empirical data was used semi structured interviews. This method allowed participants to discuss their experiences with AI-supported decision-making, governance practices, and trust formation while providing sufficient consistency across interviews to support comparative analysis. The flexibility of the interview format also enabled participants to introduce practical examples from their own organizations, generating insights that may not have emerged through more structured methods.

In addition to the interviews, the study incorporated three organizational case studies: Amazon, COMPAS, and Netflix. These cases were selected because they represent different applications of AI and illustrate both the opportunities and challenges associated with AI-supported decision-making. Examining multiple cases enabled the study to explore issues related to decision performance, governance practices, algorithmic accountability, and human oversight across different organizational contexts.

The combination of interviews and case studies strengthened the research through methodological enrichment. Interview data provided insights into managerial perceptions and experiences, while case study-based evidence offered practical examples of AI implementation and governance outcomes. Comparing findings across these sources supported the identification of recurring themes and increased confidence in the analytical conclusions.

Overall, the selected research strategy aligned closely with the objectives and research questions of the study. By integrating managerial perspectives with organizational evidence, the methodology provided a broader understanding of how AI influences decision-making effectiveness, governance maturity, and human–AI collaboration within contemporary organizations.

## 3.6 Data Analysis Methodology

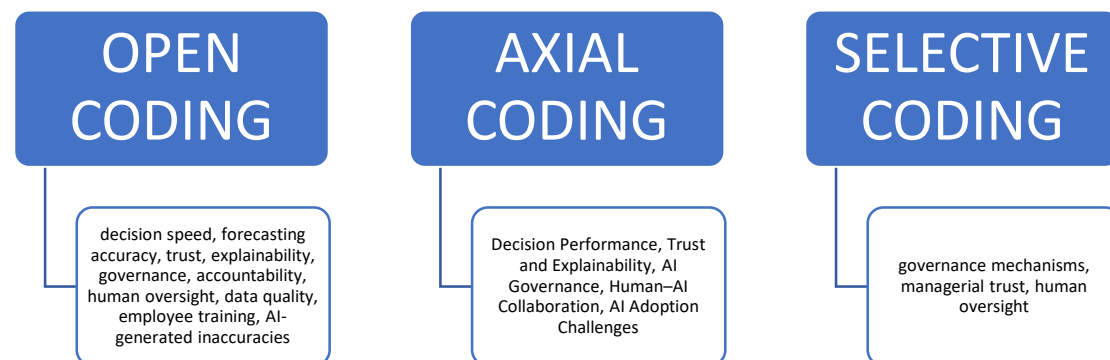
The qualitative data collected through the semi-structured interviews were analyzed using thematic analysis supported by a structured manual coding process. Thematic analysis was selected because it provides a systematic approach for identifying, organizing, and interpreting patterns within qualitative data while allowing sufficient flexibility to capture unexpected insights. This method was considered particularly appropriate for exploring managerial experiences and organizational practices related to AI-supported decision-making.

Due to the limited number of interviews ( $n = 5$ ), manual coding was considered appropriate and allowed to engage directly with the data throughout the analysis process. This approach facilitated close examination of participant responses and supported the identification of recurring concepts related to AI adoption, governance practices, managerial trust, and decision-making effectiveness.

The analysis followed a three-stage coding procedure consisting of open coding, axial coding, and selective coding. During the first stage, open coding was used to identify recurring concepts and ideas emerging from the interview data. Examples of initial codes included decision speed, forecasting accuracy, trust, explainability, governance, accountability, human oversight, data quality, employee training, and AI-generated inaccuracies.

The second stage involved axial coding, where related codes were grouped into broader analytical categories. This process resulted in the development of five main themes: Decision Performance, Trust and Explainability, AI Governance, Human–AI Collaboration, and AI Adoption Challenges. These themes reflected the most frequently discussed issues across the interviews and provided the foundation for the subsequent analysis.

In the final stage, selective coding was applied to integrate the themes into a broader conceptual understanding of AI-supported decision-making. This stage focused on identifying relationships between the themes and examining how governance mechanisms, managerial trust, and human oversight influence the effectiveness of AI adoption within organizational settings. The findings from this process contributed directly to the development of the AI Decision Governance Framework presented later in the study.



Throughout the analysis, interview responses were continuously compared against emerging themes in a continuous process. This approach supported consistency in coding decisions and ensured alignment between the empirical findings, the research objectives, and the theoretical framework developed in the literature review. The structured coding process also strengthened the credibility of the analysis by providing a clear link between participant responses, thematic findings, and the study's overall conclusions.

### 3.7 Interview Analysis and Coding Framework

The coding framework was developed to organize the interview findings into meaningful analytical categories that aligned with the objectives of the study. Following the coding process described in the previous section, recurring concepts identified in the interview data were grouped into broader themes that reflected the key dimensions of AI-supported decision-making.

The analysis resulted in five main thematic categories: Decision Performance, Trust and Explainability, AI Governance, Human–AI Collaboration, and AI Adoption Challenges. These themes emerged consistently across the interviews and captured the issues most frequently discussed by participants, including decision effectiveness, transparency, accountability, human oversight, and challenges associated with AI adoption.

### ***Coding Framework***

| <b>OPEN CODES</b>                                    | <b>AXIAL THEMES</b>      |
|------------------------------------------------------|--------------------------|
| Decision speed, Forecasting accuracy, Risk detection | Decision Performance     |
| Trust, Explainability, Transparency                  | Trust and Explainability |
| Governance, Accountability, Compliance               | AI Governance            |
| Human oversight, Managerial judgment                 | Human–AI Collaboration   |
| Hallucinations, Data quality, Training gaps          | AI Adoption Challenges   |

The coding framework provided a structured basis for interpreting the interview data and identifying relationships between the different themes. It also supported the organization of the findings presented in Chapter 4 and contributed to the development of the AI Decision Governance Framework discussed later in the study.

## 3.8 Reliability and Validity

The aim of the qualitative research were to be reliable and valid. The structured analytical process, including manual coding and transparent documentation supported reliability. The use of coding framework contributes to consistent data interpretation because similar patterns analyzed in a comparable way across all the interviews.

For achieving analytical consistency used three coding processes. The stages were open coding, axial coding, and selective coding further enhanced analytical consistency. This structured approach helped to evaluate managers interview responses to wider concepts, while maintaining the focus in the research and the objectives in theoretical framework. The different professional backgrounds amplify the validation of the outcome. The diversity of perspectives supported by cross case comparison and provided a broader understanding of how AI adoption, governance practices, trust, and human–AI collaboration is experienced across different environments.

## 3.9 Ethical Considerations

This study adhered to established ethical principles for academic research involving human participants. Prior to participation, all interviewees were informed about the purpose of the study, the voluntary nature of their involvement, and their right to withdraw from the research at any stage without consequence. Informed consent was obtained from all participants before the interviews were conducted. Participants were also informed that the information provided would be used solely for academic research purposes.

Participant anonymity and confidentiality were maintained throughout the study. Personal identifiers were removed from interview records, and participants were referenced using anonymized labels (e.g., Participant1–Participant5) rather than identifiable information. These measures were implemented to protect professional identities and encourage open discussion of organizational practices, decision-making processes, and experiences related to AI adoption.

All interview data were securely stored and accessed only by the researcher. Digital files were protected through password-controlled storage systems, and all collected information was used exclusively for the purposes of this research. Appropriate data handling procedures were followed to support both ethical compliance and research integrity.

The researcher also assumed responsibility for the accurate and respectful interpretation of participant perspectives. Care was taken to avoid selective reporting, misrepresentation, or distortion of interview responses. The findings were presented in a manner that reflected the diversity of participant experiences while maintaining analytical objectivity and consistency with the collected data. Overall, adherence to ethical research principles contributed to the credibility, trustworthiness, and academic integrity of the study.

## 3.10 Methodological Limitations

As with any research design, this study is facing several methodological limitations that should be considered when interpreting the findings. First, the qualitative nature of the research limits the extent to which the results can be statistically generalized to wider populations. The study was based on a relatively small interview sample ( $n = 5$ ), which was selected to provide in-depth insights rather than statistical representation. Consequently, the findings should be interpreted as context-specific observations rather than universally applicable conclusions.

Second, differences in organizational context, industry characteristics, and levels of AI adoption maturity may have influenced participant experiences and perceptions. Organizations vary considerably in terms of technological capabilities, governance structures, and decision-making practices. As a result, the experiences reported by participants may not fully reflect the conditions present in other organizational settings. Nevertheless, the inclusion of participants from different professional backgrounds provided valuable comparative perspectives and enriched the analysis.

Third, the study relied partly on personal experience interview data. Participant responses may have been influenced by their past, the culture of their business, professional responsibilities, or individual attitudes toward AI technologies. Although such perspectives

provide valuable qualitative insights, they may also introduce elements of subjective interpretation. To reduce this limitation, interview findings were compared with evidence derived from organizational case studies and secondary data sources.

Another limitation relates to the use of secondary data for the development of the case studies. While the selected cases were supported by extensive academic and industry documentation, the analysis depended on publicly available information rather than direct organizational access. This may have restricted the depth of insight available for certain implementation and governance practices.

Despite these limitations, the chosen methodology offered significant advantages for exploring a complex and evolving phenomenon such as AI-supported managerial decision-making. The combination of semi-structured interviews, case study analysis, and thematic coding enabled an in-depth examination of governance practices, trust formation, and human–AI collaboration within real organizational contexts. The objective of the study was therefore to achieve analytical and theoretical generalization rather than statistical generalization, contributing to a deeper understanding of AI adoption and decision governance.

Overall, acknowledging these limitations enhances the transparency, credibility, and academic status of the research while providing an appropriate context for interpreting the findings presented in the following chapter.

## 4.1 Introduction

The empirical findings are presented and analyzed in this chapter. They derived from the semi-structured interviews conducted with professionals working in AI-supported decision-making environments, as well as the selected organizational case studies examined in the research. The purpose of this chapter is to identify repeated patterns emerging from the data and to interpret these findings in relation to managerial decision-making, the governance practices, trust formation, and human with AI collaboration.

The analysis is structured according to the above coding framework presented in Chapter 3. Following the coding process, five main themes emerged from the interview data: Decision Performance, Trust and Explainability, AI Governance, Human–AI Collaboration, and AI Adoption Challenges. These themes provided the analytical foundation for interpreting the empirical findings and examining how organizations integrate AI into managerial decision processes.

The findings suggest that AI contributes to a faster analysis and has improved forecasting capability. Also, AI has enhanced the decision support system. At the same time, participants highlighted several challenges associated with AI adoption. Transparency is a big concern for managers to understand how data and in what quality are produced. Also, they facing the risk of inaccurate outputs generated by AI systems. The results further indicate that governance mechanisms, managerial trust, and human oversight play a critical role in determining the effectiveness of AI-supported decision-making.

The chapter is organized into sections that reflect the thematic structure of the analysis. Section 4.2 examines the impact of AI on decision performance, focusing on decision speed the analytical capability and on how accurate the forecast is. Section 4.3 explores the trust and explainability highlighting the factors that influence managerial confidence in AI-generated recommendations. Section 4.4 investigates how governance practices and risk management mechanisms are used to support responsible AI adoption. Section 4.5 analyses the evolving relationship between human judgment and AI systems within organizational decision environments. Finally, Section 4.6 integrates the findings from the organizational case studies and presents a cross-case analysis of the main patterns and implications identified throughout the research.

By combining interview evidence with case study findings, the chapter provides a broader understanding of how technological capability, governance maturity, and human decision processes interact to shape AI adoption outcomes within contemporary organizations.

## 4.2 AI and Decision Performance Transformation

A common theme across the interviews was the positive impact of AI on decision speed and analytical capability. Most participants reported that AI helped them process large amounts of information more quickly and identify patterns that would be difficult to detect through

manual analysis alone. This was considered particularly valuable in environments where decisions need to be made quickly and where large volumes of data are involved. Several of them noted that AI reduced the time spent on routine analytical tasks because it has allowed managers to be more focused on evaluation, the planning, and decision-making.

Participants also highlighted the role of AI in improving forecasting and planning activities. Interviewers working in risk management and analytical roles reported that predictive models helped identify potential risks earlier and supported scenario analysis. These capabilities were viewed as useful for reducing uncertainty and improving the quality of managerial decisions. Several participants stated that AI-generated insights increased their confidence when evaluating future trends and potential business outcomes.

At the same time, participants emphasized that AI-generated recommendations were not used as the final decision. A repeated finding across the interviews was that managers continued to review and validate AI outputs before taking action. Respondents explained that human judgment remained important when decisions involved strategic priorities and involves ethical concerns because AI has significant business consequences. In practice, AI was viewed as a decision support tool rather than a replacement for managerial responsibility.

Several interviewers also noted that AI contributed to be more consistent in decision-making processes. By applying the same analytical logic across large datasets, AI systems helped reduce variations that may arise from individual judgment or cognitive bias. However, participants stressed that the quality of decisions still depended on the quality of the underlying data and the ability of managers to interpret AI-generated outputs correctly.

Overall, participants viewed AI as a tool that strengthens decision-making rather than automates it completely. The findings suggest that improvements in decision speed, forecasting capability, and analytical consistency are most effective when combined with human oversight, contextual understanding, and managerial experience.

## 4.3 Trust Formation and the Role of Explainability

Trust emerged as one of the most frequently discussed themes across the interviews. Participants consistently reported that their willingness to use AI-generated recommendations depended on how reliable and understandable they perceived the system to be. Most respondents explained that trust was not established immediately but developed over time through repeated use and positive experience with AI-supported decisions.

Several participants highlighted the importance of transparency and explainability in building confidence in AI systems. Interviewees stated that they were more comfortable relying on AI recommendations when they could understand the factors behind the output or review the information used to generate it. Visual dashboards, performance reports, and clear explanations were frequently mentioned as features that improved confidence and reduced uncertainty.

In contrast, participants expressed greater hesitation when dealing with systems that appeared difficult to understand or provided limited information about how

recommendations were produced. Some respondents explained that they were less likely to rely on AI outputs when the reasoning behind a recommendation was unclear. In such cases, additional verification and managerial review were often required before a decision could be made.

A recurring theme across the interviews was that trust was closely linked to explainability. Participants generally agreed that transparency helped them assess the reliability of AI-generated insights and increased their willingness to incorporate those insights into decision-making processes. Several interviewees also noted that trust was strengthened when AI recommendations were consistent with their professional experience and business knowledge.

The findings further suggest that trust is influenced by organizational factors in addition to technical characteristics. Participants highlighted the role of leadership support, employee training, and communication regarding AI capabilities and limitations. Organizations that invested in user education and provided guidance on the appropriate use of AI were perceived as more successful in encouraging acceptance of AI-supported decision tools.

Overall, the findings indicate that trust plays an important role in determining how managers use AI-generated recommendations. Participants viewed explainability, transparency, and system reliability as key factors supporting trust formation. At the same time, organizational support and user understanding were considered equally important for the effective integration of AI into managerial decision-making.

## 4.4 Emerging AI Governance Practices

The findings indicate that many organizations are currently operating at early or intermediate stages of AI governance maturity. While most organizations have implemented some level of validation, monitoring, or compliance processes, fully integrated enterprise-level AI governance frameworks remain relatively uncommon. Participants frequently have described governance structures as an evolving process rather than fully applied. Reflecting the relatively recent integration of AI into core organizational decision processes.

These findings suggest that governance capability functions as a key factor of effective AI-supported decision-making. Governance maturity appears strongly linked to the size of the organization and how exposed it is to regulations. At the scale of AI adoption, it is indicated that governance development evolves alongside technological integration. The results reinforce the importance of structured governance frameworks capable of aligning performance optimization, risk management, and accountability across the AI decision lifecycle, providing a foundation for the framework development presented in the following chapter.

## 4.5 Human–AI Collaboration and Decision Authority

### Distribution

A repeated theme across the interviews was the importance of collaboration between AI systems and human decision-makers. Participants consistently reported that AI was used to support decision-making by providing analytical insights made forecasts and recommendations. However, final decision authority remained with managers, particularly in situations involving high business risk or had strategic importance or ethical considerations.

Several participants explained that AI was valuable for processing large volumes of data and identifying patterns that might otherwise be overlooked. At the same time, managers were responsible for interpreting results, evaluating organizational priorities, and considering factors that could not easily be captured by data alone. Respondents therefore viewed AI as a decision support tool rather than a substitute for managerial judgment.

The findings also suggest that the level of human involvement varies according to the type of decision being made. Participants reported that routine and data-intensive decisions often involve greater reliance on AI-supported recommendations. In contrast, decisions with significant financial, strategic, reputational, or ethical implications typically require additional human review and validation before action is taken.

Several interviewees emphasized that human oversight remains necessary even when AI systems demonstrate high levels of accuracy. Participants referred to situations where contextual understanding, stakeholder interests, or organizational priorities influenced the final decision. In these cases, managerial experience and professional judgment were considered essential complements to AI-generated insights.

Another theme that emerged from the interviews was the importance of continuous interaction between users and AI systems. Participants noted that effective collaboration improves over time as managers become more familiar with system capabilities and limitations. Training, experience, and feedback were viewed as important factors supporting more effective use of AI within decision-making processes.

Overall, the findings indicate that organizations are moving toward hybrid decision-making models in which AI and human managers perform complementary roles. Participants generally agreed that AI contributes analytical capability and efficiency, while managers provide contextual understanding, accountability, and strategic judgment. This balance was viewed as essential for achieving effective and responsible decision-making outcomes.

## 4.6 Case Study

### 4.6.1 Amazon

#### **Artificial Intelligence–Driven Managerial Decision-Making in Supply Chain and Customer Personalization**

## **Introduction: Controversy and Problems Addressed**

The use of Artificial Intelligence (AI) in large organizations has created both opportunities and concerns. As companies increasingly rely on AI to support business decisions many questions have emerged regarding transparency and accountability. The growing role of automated systems in organizational processes is big issue. Amazon is one of the most prominent examples of large-scale AI adoption and has often been discussed in relation to issues such as customer data usage, employee monitoring, and the transparency of algorithmic decision-making.

Despite these concerns, Amazon's investment in AI was driven by practical business challenges. The company operates in a highly complex environment involving millions of products, large-scale inventory management, rapidly changing customer demand, and intense pricing competition. Managing this level of complexity through traditional analytical methods would be extremely difficult. As a result, Amazon increasingly adopted AI technologies to support themes as forecasting, logistics, pricing decisions, and customer personalization.

For this reason, Amazon provides a useful example of how AI can improve managerial decision-making while also creating new challenges related to governance, accountability, and organizational oversight.

## **Historical Development and Organizational Context**

Amazon was founded in 1994 as an online bookstore and gradually evolved into one of the world's largest technology retail and logistics companies. As the business expanded, the volume of products and the customers transactions increased significantly. This growth created new operational and managerial challenges that could no longer be addressed effectively through traditional analytical approaches alone.

An important milestone was the launch of Amazon Web Services (AWS) in 2006, which strengthened the company's data processing capabilities and supported the development of machine learning applications. Over time, AI became an important part of many business activities including demand forecasting and inventory management. Logistics planning, fraud detection, customer recommendations, and pricing decisions are crucial.

## **Application of Artificial Intelligence in Managerial Decision Processes**

Amazon uses Artificial Intelligence across several areas of managerial decision-making, particularly in activities that involve large volumes of data and require rapid analysis. One of the most important applications is demand forecasting and inventory management. AI models analyze historical sales data or seasonal trends. Also, the employees promotions and regional demand patterns are examined. Very crucial are external factors such as weather conditions. The insights generated by these systems support managerial decisions regarding inventory allocation and a negotiation planning. Logistics operations have Improved forecasting by helping reduce stock shortages and excess inventory while improving operational efficiency.

Another important application is customer personalization. Amazon's recommendation system analyses customer behavior and purchasing patterns to suggest products that are likely to be relevant to individual users. These recommendations influence decisions related

to product placement the marketing campaign and the strategies on how customers engage. Industry estimates suggest that recommendation systems contribute significantly to Amazon's sales performance, demonstrating the strategic value of AI-generated insights.

AI also plays an important role in pricing decisions. Machine learning models continuously can analyze factors such as competitor pricing the customer demand the levels of inventory and purchasing behavior. This allows Amazon to adjust prices quickly in response to changing market conditions. While managers establish pricing objectives and strategic boundaries, many pricing adjustments are executed automatically by AI systems. This provides a clear example of a hybrid decision-making environment in which humans define strategic direction while AI supports operational execution.

A further area of application is logistics and supply chain management. Amazon combines predictive analytics, robotics, and routing algorithms to improve warehouse operations and delivery planning. Managers use AI-generated insights to support decisions related to workforce allocation, route planning, and capacity management. These capabilities contribute to faster delivery times and support services such as same-day and next-day delivery.

Overall, Amazon demonstrates how AI can support managerial decision-making across multiple operational and strategic functions. Rather than replacing managers, AI systems provide analytical capabilities that help organizations process complex information, improve forecasting accuracy, and respond more effectively to changing business conditions.

### **Data, Metrics, and Performance Outcomes**

Available evidence suggests that Amazon's use of AI has generated improvements across several performance areas. Research on AI-supported forecasting in retail environments indicates that machine learning models can improve forecast accuracy compared to traditional forecasting methods. More accurate forecasts help organizations reduce the inventory errors and improve stock availability. Through AI business can support more efficient inventory management practices.

Performance improvements are also present in logistics operations. The combination of predictive analytics in automation and robotics has contributed to faster order processing and increased warehouse efficiency. These capabilities support Amazon's ability to provide rapid delivery services and manage large-scale logistics networks more effectively. As a result, AI has become an important component of the company's operational strategy.

Customer personalization has also produced measurable business benefits. Amazon's recommendation systems help identify products that are relevant to individual customers based on their behavior and purchasing history. Industry reports suggest that recommendation engines contribute significantly to online sales by improving customer engagement and supporting cross-selling opportunities. This demonstrates how AI-generated insights can influence both customer experience and business performance.

Another important outcome is scalability. Amazon operates across global markets and manages an extremely large product portfolio. AI systems enable the company to process information, monitor operations, and support decisions at a scale that would be difficult to achieve through manual analysis alone. In this context, AI functions not only as an efficiency tool but also as a capability that supports organizational growth and operational complexity.

Overall, the available evidence suggests that Amazon's adoption of AI has improved forecasting, operational efficiency, customer engagement, and scalability. These outcomes illustrate how AI can contribute to both operational performance and strategic decision-making when supported by appropriate managerial oversight and organizational capabilities.

### **Analysis: Implications for Managerial Decision-Making and Governance**

The Amazon case illustrates how AI can support managerial decision-making by improving forecasting, operational efficiency, and data analysis capabilities. The company's use of AI enables managers to process large amounts of information, identify patterns, and make decisions more quickly. These benefits are consistent with the interview findings, where participants frequently associated AI with faster analysis, improved forecasting, and enhanced decision support.

At the same time, the case demonstrates that AI does not replace managerial decision-making. Although AI systems generate recommendations and support operational decisions, managers remain responsible for interpreting results and evaluating business implications. Managers ensure the alignment to organizational objectives. This finding reflects a common theme identified across the interviews, where participants consistently described AI as a support tool rather than a replacement for human judgment.

The case also highlights how decision authority is distributed according to the type of decision being made. Operational activities such as demand forecasting, inventory management, logistics planning, and dynamic pricing rely heavily on AI-generated insights. In contrast, strategic decisions involving investments, customer policies, business priorities, and long-term organizational objectives remain under managerial control. This supports the view that effective AI adoption requires a balance between technological capability and human accountability.

Another important observation relates to governance and trust. As organizations become increasingly dependent on AI systems, issues such as transparency and data governance are important. Also, privacy and accountability become more important. Participants in the interview analysis expressed similar concerns, particularly regarding the need for human oversight and the ability to understand how AI-generated recommendations are produced. The Amazon case therefore reinforces the importance of governance mechanisms that support responsible and transparent AI use.

Overall, the case demonstrates that the greatest benefits of AI are achieved when technological capabilities are combined with managerial judgment, human oversight, and effective governance structures. These findings align closely with the main themes identified in the interview analysis, namely Decision Performance, Trust and Explainability, AI Governance, and Human–AI Collaboration.

### **Outcomes and Strategic Impact**

The available evidence suggests that Amazon's adoption of AI has contributed to improvements in operational efficiency, customer engagement, forecasting capability, and decision speed. AI has become an important component of the company's business model, supporting both day-to-day operations and broader strategic objectives. The ability to analyze large volumes of data and generate actionable insights has helped Amazon respond more effectively to changing customer needs and market conditions.

The case also demonstrates that the impact of AI extends beyond operational efficiency. AI systems support managerial decision-making by providing predictive insights, improving planning processes, and enabling more informed resource allocation. As a result, AI has become an important organizational capability that supports growth, scalability, and competitive performance.

Importantly, the findings indicate that AI does not eliminate the role of managers but changes how managerial decisions are made. Rather than focusing primarily on data collection and analysis, managers increasingly use AI-generated insights to support evaluation, planning, and strategic decision-making. At the same time, they remain responsible for setting organizational priorities, exercising professional judgment, and maintaining accountability for decision outcomes.

Overall, the Amazon case suggests that the benefits of AI are greatest when technological capabilities are combined with human oversight and effective governance practices. This observation is consistent with the findings of the interview analysis, which highlighted the importance of managerial judgment, trust, and governance mechanisms in achieving successful AI adoption.

### **Conclusion**

The Amazon case demonstrates how AI can support managerial decision-making across a wide range of operational and strategic activities. The use of predictive analytics, automation, and data-driven insights has improved forecasting, operational efficiency, and decision speed, while helping the organization manage increasing levels of complexity.

At the same time, the case shows that successful AI adoption depends on more than technological capability alone. Human oversight, managerial judgment, and effective governance remain essential for ensuring that AI-generated recommendations are used responsibly and aligned with organizational objectives. Overall, the findings reinforce the central argument of this study: organizations achieve the greatest value from AI when technological capabilities are combined with trust, governance, and human decision-making.

### **4.6.2 COMPAS**

#### **Algorithmic Bias and Governance Failure: The COMPAS Risk Assessment System**

##### **Introduction: Controversy and Managerial Challenges**

The growing use of Artificial Intelligence (AI) in decision-making has created new opportunities but has also raised important concerns regarding fairness, transparency, and accountability. One of the most widely discussed examples is the COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) risk assessment system, developed to support decision-making within the criminal justice system. The tool was designed to estimate the likelihood that an offender would reoffend and to assist judges and other decision-makers in evaluating risk.

Despite its intended benefits, the system became the subject of significant controversy after studies and media investigations raised concerns about potential racial bias and the limited transparency of its decision-making process. Critics argued that users could not fully

understand how certain risk scores were generated so it made it difficult to evaluate the fairness and reliability of the recommendations.

The COMPAS case is particularly relevant to this study because it demonstrates that strong analytical performance alone is not sufficient to ensure successful AI adoption. When transparency, accountability, and governance mechanisms are limited, organizations may face reduced trust, reputational risks, and challenges in decision legitimacy. For this reason, the case provides an important example of how governance failures can influence the effectiveness and acceptance of AI-supported decision systems.

### **Historical Development and Implementation Context**

COMPAS was introduced in the early 2000s as part of a broader effort to support evidence-based decision-making within the criminal justice system. At the time, courts and correctional agencies were seeking more consistent ways to assess offender risk and allocate resources. The objective was to reduce reliance on purely subjective judgments by incorporating data-driven assessments into decision-making processes.

The system used a range of variables such as criminal history, personal background information and behavioral indicators in order to produce risk scores. These scores were intended to support decisions related to bail, sentencing, parole, and offender supervision. Rather than replacing judges and administrators COMPAS was designed to provide an additional source of information that could assist risk evaluation and resource planning.

Over time, the system was adopted by several U.S. states and became widely used within criminal justice organizations. From an operational perspective, COMPAS offered potential benefits by standardizing risk assessments and supporting more consistent decision-making. However, concerns gradually emerged regarding the transparency of the system. Because the algorithm was not transparent and users had limited visibility into how risk scores were calculated. That practice made it difficult to fully understand or challenge the reasoning behind specific recommendations.

This lack of transparency became one of the central issues in the subsequent debate surrounding COMPAS and highlighted the importance of explainability and accountability in AI-supported decision environments.

### **Data Evidence and Emerging Concerns**

The controversy surrounding COMPAS intensified following a 2016 investigative analysis conducted by ProPublica, which examined thousands of criminal cases in Broward County, Florida. The study compared predicted risks with actual outcomes over a two-year period. The findings suggested significant concerns in prediction errors between demographic groups. Specifically, the analysis indicated that Black defendants who did not reoffend were incorrectly labeled as high risk at nearly twice the rate of White defendants, while White defendants who later reoffended were more likely to be classified as low risk.

Although the developers disputed aspects of the methodology and argued that the algorithm achieved comparable predictive accuracy across groups the debate revealed deeper concerns

regarding fairness metrics algorithmic transparency and the interpretation of predictive models in managerial decision contexts. Importantly, many decision-makers using the tool lacked sufficient understanding of how the algorithm generated its outputs, increasing the risk of over-reliance on automated scores.

### **Analysis: Implications for Managerial Decision-Making**

The COMPAS case highlights several challenges that can emerge when AI systems are used to support high-stakes decisions. One of the most important lessons is that AI systems are not automatically objective or free from bias. If the data used to train a model reflect existing inequalities or historical patterns the resulting recommendations may also contain bias. This demonstrates the importance of carefully evaluating data quality and monitoring AI systems over time.

The case also emphasizes the importance of transparency and explainability. The decision makers often need to understand not only the outcome of a recommendation but also the reasoning behind it. In the case of COMPAS, the limited visibility into how risk scores were generated made it difficult for users to fully evaluate or challenge the system's recommendations. As a result, concerns emerged regarding fairness, accountability, and decision legitimacy.

Another important issue is the risk of excessive reliance on AI-generated outputs. The case suggests that decision quality may be affected when users accept algorithmic recommendations without sufficient review or critical evaluation. This reinforces the need for human oversight, particularly in situations where decisions have significant social and ethical or even legal consequences.

The findings also highlight the importance of governance mechanisms. The controversy surrounding COMPAS was not caused solely by the technology itself but also by the absence of adequate transparency and auditing procedures. Also, important are the accountability structures. This suggests that organizations should view governance as an essential part of AI implementation rather than as a separate compliance activity.

Importantly, the lessons from COMPAS are consistent with the themes identified in the interview analysis. Participants repeatedly emphasized the importance of transparency, trust, human oversight, and governance when using AI-supported decision systems. The case therefore backs up the argument that successful AI adoption depends not only on technical performance but also on the ability of organizations to build trust, ensure accountability, and maintain appropriate managerial control over AI-generated recommendations.

### **Outcomes and Organizational Lessons**

The COMPAS case generated significant debate among the researchers the policymakers and all legal professionals in general and the wider public. The controversy raised important questions regarding fairness, transparency, accountability, and the responsible use of AI in decision-making. As a result, the case contributed to broader discussions about AI governance and encouraged the development of new approaches to algorithmic auditing in order to provide transparency and ethical protection.

An important lesson from the case is that successful AI adoption depends on more than technical performance. Even when AI systems provide useful predictions, organizations may face challenges if users do not trust the system or cannot understand how recommendations are produced. The controversy surrounding COMPAS demonstrated that concerns about fairness and explainability can significantly affect the acceptance and legitimacy of AI-supported decisions.

From a managerial perspective, the case highlights the importance of combining technological capability with governance mechanisms, human oversight, and ethical evaluation. Organizations implementing AI systems should ensure that decision-makers understand the limitations of algorithmic recommendations and retain the ability to review, question, and override system outputs when necessary.

Overall, the COMPAS case demonstrates that transparency, accountability, and trust are essential components of effective AI adoption. The lessons from this case reinforce the findings of the interview analysis, where participants consistently emphasized the importance of explainability, governance, and human oversight in building confidence in AI-supported decision systems.

### **Conclusion**

The COMPAS case demonstrates that the successful use of AI depends on more than predictive capability alone. Although AI systems can improve consistency and support decision-making, important challenges may emerge when transparency, accountability, and fairness are not adequately addressed. The controversy surrounding COMPAS illustrates how limited explainability can reduce trust and raise concerns regarding the legitimacy of AI-supported decisions.

The case also highlights the importance of governance mechanisms and human oversight in high-stakes decision environments. Overall, the findings reinforce a central argument of this study: organizations are more likely to achieve effective and responsible AI adoption when technological capabilities are supported by transparency, accountability, governance structures, and informed human judgment.

### **4.6.3 Case Study Netflix**

#### **Strategic Innovation Through Artificial Intelligence: Decision-Making Transformation at Netflix**

##### **Introduction: Innovation Context and Managerial Challenges**

The rapid growth of digital platforms has increased the complexity and depth of managerial decision-making. Industries where customer preferences change quickly and market competition is intense extra effort is needed to predict the audience likes and dislikes. In this environment the organizations must continuously evaluate large numbers of data in order to understand customer behavior, predict future demand, and make informed strategic decisions. Artificial Intelligence (AI) has become an important tool in supporting these activities.

Netflix is widely recognized as one of the most successful examples of AI-driven decision-making in the digital entertainment industry. The company uses data analytics and machine learning to support decisions related to content recommendations, customer retention,

content investment, and international expansion making their thoughts of what the audience wants reality in a global scale. By analyzing the viewing patterns and user behavior Netflix can generate insights that support both operational and strategic decision-making.

At the same time, Netflix has attracted discussion regarding the increasing role of algorithms in shaping content recommendations and influencing viewing choices. Some critics argue that excessive reliance on algorithmic recommendations may limit content diversity or reduce opportunities for creative experimentation which is the reason that these concerns highlight the importance of balancing data-driven insights with human judgment and strategic decision-making, keeping quality in the conversation.

The Netflix case is particularly relevant to this study because it demonstrates how AI can be used not only to improve operational efficiency but also to support strategic decisions under conditions of uncertainty. As a result, it provides valuable insights into the relationship between technological capability and managerial judgment. AI improves the performance of Netflix in complex environments having in mind managers skills, quality, cultures and the instinct of what is relevant nowadays or in the near future. Still through the platforms history we can understand how important AI was in its growth.

### **Historical Development and Organizational Context**

Netflix was founded in 1997 as a DVD rental company and gradually evolved into one of the world's leading streaming platforms. As the company expanded the need to understand customers preferences became increasingly important for maintaining growth and competitiveness. To support this objective, Netflix invested heavily in data analytics and machine learning capabilities and developed a business model that relies extensively on data-driven decision-making.

An important turning point occurred when Netflix shifted from content distribution to content production. Producing original content involved significant financial risk, The success depended on predicting audience preferences in a highly competitive and rapidly changing market. To reduce uncertainty, the company began using AI and predictive analysis to support content-related decisions.

By analyzing the viewers behavior and search activity it was easier to forecast completion rates and find engagement patterns. Also, and customer preferences, Netflix developed models capable of identifying trends and estimating potential audience demand. These insights were used to support decisions regarding content acquisition, original productions, marketing strategies, and international expansion.

Unlike traditional entertainment companies that often relied primarily on managerial experience and industry intuition, Netflix increasingly combined human judgment with data-driven insights. This approach enabled decision-makers to evaluate opportunities using both analytical evidence and strategic expertise, creating an environment in which AI became an important component of organizational decision-making.

The evolution of Netflix therefore provides a useful example of how AI can support strategic decisions under conditions of uncertainty while complementing rather than replacing managerial judgment.

## **Application of Artificial Intelligence in Strategic and Managerial Decisions**

Artificial Intelligence is integrated into several areas of decision-making at Netflix, particularly those related to customer engagement, rules in ownership, content strategy, and business growth. One of the most well-known applications is the company's recommendation system. By analyzing viewing behavior, search activity, the watch history, and user preferences the machine learning models generate personalized content recommendations. These recommendations help improve customer engagement and retention while also providing managers with insights into viewing trends and audience interests.

AI also supports strategic decisions related to content investment. Producing original content involves significant financial commitments and uncertainty regarding audience response. To support these decisions, Netflix uses predictive analytics to evaluate factors such as genre preferences, viewing patterns, regional demand, and audience engagement. These insights help managers assess potential opportunities and reduce investment risk when selecting new projects. Keeping in mind that the final decisions of selections is still in humans hands.

A frequently example is the development of *House of Cards*, where data analysis indicated strong audience interest based on viewing behavior, genre preferences, and the popularity of key actors. Although final decisions remained under managerial control, data-driven insights played an important role in supporting the investment process. This illustrates how AI can contribute to strategic decision-making while still requiring human judgment and creative evaluation.

Netflix also uses AI to support experimentation and continuous improvement. Through extensive A and B testing, managers can evaluate alternative design of platforms. Managers can also evaluate recommendation approaches and marketing initiatives. The results of these experiments provide evidence that supports decision-making and helps the organization refine products and services over time for their customers.

Overall, Netflix demonstrates how AI can support both operational and strategic decisions. Rather than replacing managers, AI provides analytical insights that reduce uncertainty, improve understanding of customer behavior, and support more informed decision-making in a highly competitive and rapidly changing industry.

## **Data, Metrics, and Performance Outcomes**

The use of AI at Netflix has been associated with improvements across several performance areas. One of the most visible outcomes relates to content recommendations. Industry reports suggest that a large proportion of the content viewed on the platform is influenced by personalized recommendation systems, highlighting the importance of AI in shaping customer engagement and viewing behavior.

Personalization has also contributed to customer retention. By recommending content that aligns with individual preferences, Netflix can improve user satisfaction and reduce subscriber discomfort. This creates significant business value, as can retain existing customers is generally more cost-effective than gaining new ones. As a result, recommendation systems have become an important component of the company's growth strategy.

As we mentioned AI-supported decision-making also contributes to content investment efficiency. Predictive analytics help managers evaluate audience preferences and identify

content opportunities with greater confidence. Although success in the entertainment industry can never be guaranteed, data-driven insights help reduce uncertainty and support more informed investment decisions. However, final investment decisions remain under managerial control, illustrating the complementary relationship between AI-generated insights and human judgment.

In addition, continuous experimentation through A/B testing enables managers to improve platform design, customer experience, and marketing effectiveness based on observed user behavior. These capabilities allow decision-makers to evaluate alternatives using empirical evidence rather than relying solely on assumptions or intuition.

Another important outcome is the ability to operate at a global scale while responding to local market preferences. Netflix serves audiences in more than 190 countries, each with different viewing habits and cultural preferences. AI-generated insights help managers understand regional trends and adapt content strategies accordingly. This combination of large-scale data analysis and localized decision-making has become an important strategic capability for the organization.

Overall, the available evidence suggests that AI has helped Netflix improve customer engagement. Also, AI supports regarding content investment decisions and strengthens its ability to operate in diverse international markets. The case demonstrates how AI can support both strategic and operational decision-making while reducing uncertainty and enhancing managerial insight. At the same time the findings suggest that the greatest value is achieved when data-driven recommendations are combined with human judgment and strategic oversight.

### **Analysis: Managerial Implications and Strategic Innovation**

The Netflix case shows us how AI can create strategic decision-making in environments characterized by uncertainty and rapidly changing customer preferences by examining large volumes of user data. AI systems can provide insights that help managers identify trends and evaluate new opportunities. With AI usage managers can make more informed decisions regarding content investments, customer engagement, and market expansion. These capabilities reduce uncertainty and support more effective resource allocation.

At the same time, the case highlights that AI functions as a support tool rather than a factor which replaces judgment and decision making by managers. Although predictive models can identify patterns and estimate audience demand, the managers remain responsible for evaluating strategic opportunities. Managers assess business risks and make the final investment decisions. This finding is consistent with the interview results, where participants emphasized the importance of combining AI-generated insights with human experience and contextual understanding.

Another important observation relates to organizational learning and experimentation. Netflix has developed a culture in which decisions are continuously evaluated through data analysis and testing. The extensive use of A and B testing allows managers to compare alternatives and learn from user behavior. AI decisions are refined over time. This approach demonstrates how AI can support adaptive decision-making and continuous improvement within organizations.

Overall, the Netflix case demonstrates that AI can create value not only through operational efficiency but also through strategic innovation. All research findings suggest that organizations achieve the greatest benefits when analytical capabilities are combined with managerial judgment, experimentation, and effective governance practices. These observations align closely with the themes identified in the interview analysis, particularly Decision Performance, Human–AI Collaboration, and AI Governance.

### **Outcomes and Strategic Impact**

The incorporation of AI into Netflix's decision-making processes has contributed to improvements in customer engagement. The content investment decisions and business performance were upgraded. By using predictive analytics and personalized recommendation systems, the company has been able to better understand customer preferences and support planning for content. The responses are more effectively to changing market conditions. These capabilities have strengthened Netflix's ability to compete in a highly dynamic global industry.

An important outcome of the case is the demonstration that AI can support strategic decision-making by reducing uncertainty and providing managers with valuable insights which clear the uncertainties. At the same time, the findings show that AI does not replace managerial expertise. Managers continue to play a central role in evaluating opportunities, making investment decisions, and ensuring that business strategies remain aligned with organizational objectives, as we analyzed previously who takes the final decision is the managers responsibility.

Not only that, the case also illustrates that the greatest value is achieved when technological capabilities and human judgment and creativity work together. This combination enables organizations to make more informed decisions while maintaining flexibility and innovation.

Overall, the Netflix case demonstrates how AI can become a source of strategic advantage and innovation in new systems automation. when supported by effective managerial oversight, continuous learning, and appropriate governance practices.

### **Conclusion**

Bottom line is that the Netflix case demonstrates how AI can support both operational and strategic decision-making within a highly competitive and rapidly changing industry. Through the use of predictive analytics, personalization, and continuous experimentation, the company has improved customer engagement, supported content investment decisions, and reduced uncertainty in key business activities.

Overall, the Netflix case reinforces the central argument of this study: AI creates the most value when technological capabilities, human judgment, and governance mechanisms operate together to support effective and responsible decision-making in a world that speed in every shade and every field of business is crucial.

## **4.7 Cross-Theme Analytical Integration**

Both interviews and case studies indicating that common patterns emerging regarding AI in businesses. The capabilities of technology are not enough for a successful AI execution. When appropriate structure and respect in governance exists, then better results can be

achieved. The key factor in decision making when assisted by AI is always the human's ability to oversight and cross check data evaluation. Across all interviews, participants referred to AI as a useful tool assisting decision making rather than replacing the human factor. Netflix and Amazon case studies confirm the need of human and AI collaboration, where AI tools generated insights through processing large volumes of data, while managers kept accountability for company's strategic vision and compliance with ethical values. So, the results will basically determine a kind of hybrid decision at the end of the process that keep managers certain and the company happy.



## 5.1 Introduction

This chapter integrates the empirical findings of the study with the broader literature on Artificial Intelligence and managerial decision-making. The organizational governance and human–AI collaboration are also analyzed. The purpose is not merely to restate the findings but to interpret them within a wider theoretical context and to develop a coherent understanding of how AI can be integrated effectively and responsibly into organizational decision processes. By connecting the empirical evidence with existing theoretical perspectives, the chapter contributes to a deeper understanding of AI-enabled managerial decision environments.

Building upon the findings presented in Chapter 4, the chapter develops the proposed AI Decision Governance Framework and examines its theoretical and managerial implications. The discussion explores how the empirical results contribute to current debates regarding the decision augmentation with AI tools. Governance maturity and trust formation also needs to be improved with human and AI collaboration. Particular attention is given to the organizational conditions that enable AI systems to improve decision performance while maintaining transparency, accountability, and effective human oversight.

The chapter also introduces the AI Decision Effectiveness and Assurance Index (AI-DEAI) as a conceptual evaluation approach derived from the study's findings. Rather than functioning as a validated measurement instrument, AI-DEAI is proposed as a multidimensional framework that organizations may use to assess the effectiveness and governance maturity. Trustworthiness of AI needs improvement to support decision environments. The model integrates the key dimensions identified throughout the research, including decision performance, trust and explainability, governance practices, human oversight, and organizational readiness for AI adoption.

The chapter is structured as follows. First, the findings are discussed in relation to decision-making theory, governance capability, trust development, and socio-technical perspectives. Second, the AI Decision Governance Framework is presented and theoretically justified. Third, the proposed AI-DEAI model is introduced as a conceptual assessment mechanism for AI-supported decision environments. Finally, the chapter discusses managerial implications, theoretical contributions, research limitations, and future research directions before presenting the overall conclusions of the study.

## 5.2 Interpretation of Findings in Relation to Decision-Making Theory

The findings of this study suggest that Artificial Intelligence functions primarily as a decision support and decision augmentation tool rather than a replacement for managerial decision-making. Across the interviews, participants consistently reported that AI improves analytical

capability, forecasting accuracy, and decision speed. At the same time, they emphasized the continued importance of human judgment when interpreting results, evaluating risks, considering ethical implications, and making strategic decisions. These findings indicate that AI contributes to decision effectiveness but does not eliminate the need for managerial involvement.

From a theoretical perspective, the findings are consistent with bounded rationality theory, which argues that decision-makers operate under limitations related to information availability, time constraints, and cognitive capacity. The results suggest that AI can help managers overcome some of these limitations by processing large volumes of data and identifying patterns that may be difficult to detect through traditional analysis. In this sense, AI extends managerial analytical capability rather than replacing managerial reasoning.

The findings also support the concept of augmented intelligence, which emphasizes collaboration between human expertise and technological capability. Evidence from both the interviews and the case studies suggests that the most effective decision environments are those in which AI provides analytical support while managers retain responsibility for interpretation, contextual evaluation, and final decision-making. This pattern was evident across the Amazon and Netflix cases, where AI-generated insights supported decision processes but did not replace managerial accountability.

Another important finding concerns the role of governance in decision effectiveness. Participants frequently associated trust in AI systems with transparency, explainability, and the presence of human oversight mechanisms. Organizations that established clear governance practices appeared more confident in integrating AI into decision processes, while concerns regarding accountability and explainability often resulted in increased verification and reduced reliance on AI-generated outputs. These findings are consistent with socio-technical systems theory, which emphasizes that organizational outcomes depend on the interaction between technology, people, and organizational structures.

Overall, the findings suggest that effective AI-supported decision-making emerges from the interaction between technological capability, governance practices, and human judgment. Rather than viewing AI adoption as a purely technological initiative, the evidence indicates that successful implementation requires the integration of technological systems with organizational processes and managerial expertise. This perspective provides an important foundation for the AI Decision Governance Framework developed later in this chapter.

## 5.3 Trust, Transparency and Explainability in AI-Supported Decision Environments

Trust emerged as one of the most important factors influencing the adoption and use of AI-supported decision systems. Across the interviews, participants repeatedly emphasized that their willingness to rely on AI-generated recommendations depended on how much they understood the system and how confident they were in its outputs. Trust was influenced not only by the accuracy of AI recommendations but also by transparency, explainability, data quality, and previous experience with the technology.

The findings suggest that managers are more likely to use AI-generated insights when they can understand how recommendations are produced. Participants expressed greater confidence in systems that provide clear explanations, visual representations, or transparent decision processes. In these situations, AI was viewed as a useful decision support tool that enhanced analytical capability without reducing managerial control. This finding is consistent with the literature on explainable AI, which highlights the importance of transparency in supporting user confidence and responsible decision-making.

At the same time, the results indicate that limited transparency can reduce trust and increase reliance on manual verification. Several participants reported that they were less willing to accept AI recommendations when the reasoning behind the output was unclear. Similar concerns were evident in the COMPAS case study, where limited explainability contributed to questions regarding fairness, accountability, and decision legitimacy. The case demonstrated that technical performance alone is often insufficient to ensure acceptance if users cannot understand or evaluate how decisions are generated.

The findings also highlight the relationship between trust and governance. Participants generally reported higher levels of confidence when organizations had established clear oversight procedures, accountability structures, and monitoring mechanisms. This suggests that trust is shaped not only by technical characteristics but also by the broader organizational environment in which AI systems operate.

Overall, the findings indicate that transparency and explainability play an important role in building trust and supporting effective AI adoption. Organizations that invest in explainable systems, clear communication, and appropriate governance practices appear better positioned to integrate AI into decision-making processes while maintaining managerial confidence and accountability. These findings support the inclusion of Trust and Explainability as a core dimension of the AI Decision Governance Framework developed in this study.

## 5.4 Governance Maturity and Ethical Decision Integration

The findings indicate that while most organizations recognize the importance of AI governance, many remain at an early stage of governance maturity. Participants frequently described operational governance practices such as data quality controls, model validation procedures, and performance monitoring. However, more comprehensive governance approaches that integrate ethical oversight, accountability mechanisms, transparency practices, and continuous evaluation were less common. This suggests that governance development progress less than technological adoption.

The results highlight the importance of governance as a supporting factor for effective AI adoption. Participants reported greater confidence in AI-supported decisions when clear oversight procedures and accountability structures existed. Also, monitoring mechanisms were in place. In contrast, uncertainty regarding responsibility, explainability, or decision validation often resulted in increased human verification and reduced reliance on AI-generated recommendations.

Ethical considerations also emerged as an important aspect of AI-supported decision-making. Participants expressed concerns regarding algorithmic bias, data privacy, accountability, and the potential consequences of inaccurate AI outputs. These concerns were particularly evident in situations involving high-impact decisions or regulated environments. The findings suggest that ethical evaluation is increasingly becoming part of managerial decision processes rather than being treated solely as a compliance requirement.

The case studies further reinforced the importance of governance maturity. The Amazon case demonstrated how structured oversight and decision processes can support effective AI integration, while the COMPAS case illustrated the risks associated with limited transparency and insufficient accountability mechanisms. Together, these cases suggest that governance plays an important role in determining whether organizations can translate AI capabilities into reliable and trusted decision outcomes.

The findings also indicate that governance should not be viewed solely as a risk management function. Organizations with stronger governance practices appeared more willing to integrate AI into decision-making processes and demonstrated higher levels of trust in AI-generated recommendations. This suggests that governance can support both responsible AI use and improved decision performance.

Overall, the results indicate that governance maturity is closely linked to organizational trust, accountability, and decision effectiveness. Effective AI adoption therefore requires more than technological capability alone. Organizations must also develop governance structures that support transparency, ethical decision-making, human oversight, and continuous monitoring. These findings provide an important foundation for the AI Decision Governance Framework developed later in this chapter.

## 5.5 Human–AI Collaboration and Decision Authority

### Structures

The findings indicate that hybrid human–AI decision models represent the dominant approach to AI integration within organizations. Across the interviews, participants consistently described AI as a tool that supports decision-making rather than replacing managerial responsibility. While AI systems provide analytical insights, predictive capabilities, and data-driven recommendations, managers continue to retain final decision authority, particularly in situations involving uncertainty, strategic importance, or ethical considerations.

A recurring theme throughout the findings was the importance of human oversight. Participants emphasized that AI-generated recommendations require interpretation of the context and validation before being incorporated into organizational decisions. This was particularly evident in high-risk environments where errors may have significant financial, operational, legal, or reputational consequences. Human involvement therefore functions not only as a control mechanism but also as a means of ensuring that decisions remain aligned with organizational objectives and stakeholder expectations.

The findings also suggest that decision authority should be distributed according to the nature of the decision. Routine and data-intensive operational decisions can often be supported extensively by AI systems due to their ability to process large volumes of information quickly and consistently. In contrast, strategic decisions involving uncertainty, ethical implications, stakeholder interests, or long-term organizational priorities continue to require stronger managerial involvement. This pattern was evident in both the interview findings and the organizational case studies, particularly in the Amazon and Netflix cases, where AI supported decision processes while managers retained responsibility for strategic direction and final decision-making.

Another important finding concerns the need for clearly defined roles and responsibilities within AI-supported decision environments. Participants reported greater confidence in AI systems when organizations established clear accountability structures, validation procedures, and escalation mechanisms. These governance practices help reduce uncertainty regarding decision ownership and support more effective collaboration between human decision-makers and AI systems.

The findings further indicate that human–AI collaboration improves over time through learning and experience. As managers become more familiar with AI systems, they develop a better understanding of system capabilities and limitations, allowing them to use AI-generated insights more effectively. This process contributes to improved trust, more efficient decision-making, and stronger integration of AI into organizational processes.

Overall, the results suggest that effective AI adoption depends on achieving an appropriate balance between technological capability and human judgment. Rather than replacing managers, AI appears to create the greatest value when integrated into collaborative decision structures that combine analytical precision with contextual understanding, ethical evaluation, and strategic oversight. These findings support the inclusion of Human–AI Collaboration as a core dimension of the AI Decision Governance Framework proposed in this study.

## 5.6 AI Decision Governance Framework

Based on the empirical findings and theoretical insights, this study proposes the AI Decision Governance Framework as an integrated conceptual model for understanding how organizations can achieve effective and responsible AI-supported decision-making. The framework is derived from the findings of the interviews, thematic analysis, and organizational case studies and reflects the key dimensions that emerged consistently throughout the research.

The framework is considering Artificial Intelligence not as an isolated technological tool but as part of a broader organizational decision ecosystem in which technology, governance structures, and human decision-makers interact continuously. The findings suggest that effective AI adoption depends on the alignment of five interrelated dimensions:

### **1. Decision Performance**

This dimension focuses on the contribution of AI to improve decision speed and forecasting with more accuracy. Also evaluates the analytical capability, the operational efficiency and on how consistent the decision is.

## **2. Trust and Explainability**

This dimension testing how transparent reliable and easy to explain are the AI output.

User confidence in AI-generated recommendations and how trust influences managerial willingness to rely on AI-supported decisions.

## **3. Governance and Accountability**

This dimension examines the monitoring mechanisms and the accountability structures that exist to comply with the procedures, ethical oversight, and risk management practices that support responsible AI implementation.

## **4. Human–AI Collaboration**

This dimension considering the volume of the complementary relationship between AI systems and managerial judgment. In what level is the Human oversight and decision validation and in what level is AI tools. Also examines the interpretation generated by AI in comparison to managers and in what extend are AI tools necessary for managers.

## **5. Organizational Readiness**

This dimension examines how trained are the employers, do they have AI literacy. The data used by the organization do they quality. The leadership in what extend is supporting this transformation.

The framework proposes that these dimensions collectively should be examine in what volume AI-Supported tools are effective in the working field. which represents the central outcome of successful AI integration. Decision effectiveness is achieved when organizations combine technological capability with governance maturity, managerial trust, human oversight, and organizational readiness.

The findings further suggest that governance plays a particularly important coordinating role within the framework. Organizations that establish clear accountability structures, monitoring procedures, and transparency mechanisms appear better positioned to translate AI capabilities into improved decision outcomes. In this sense, governance functions not only as a control mechanism but also as an enabling factor supporting trust, collaboration, and decision performance.

Another important feature of the framework is its dynamic nature. As organizations gain experience with AI systems, trust develops, governance practices mature, and human–AI collaboration becomes more effective. Continuous learning and feedback mechanisms therefore contribute to the long-term improvement of AI-supported decision environments.

From a theoretical perspective, the framework integrates concepts from decision-making theory, socio-technical systems theory, governance research, and augmented intelligence literature. From a managerial perspective, it provides a structured approach that organizations can use to guide AI adoption while balancing performance objectives with transparency, accountability, and responsible oversight.

## 5.7 AI Decision Effectiveness and Assurance Index (AI-DEAI)

### 5.7.1 Conceptual Rationale

Building upon the AI Decision Governance Framework, this study proposes the AI Decision Effectiveness and Assurance Index (AI-DEAI) as a conceptual assessment model designed to support the evaluation of AI-supported decision environments. The purpose of the AI-DEAI is not to provide a validated measurement instrument but to propose a structured approach for assessing the key organizational dimensions that influence the effectiveness and trustworthiness of AI-supported decision-making.

The development of the AI-DEAI is based directly on the empirical findings of this study. The interviews, thematic analysis, and case studies consistently highlighted five dimensions that influence successful AI adoption: decision performance, trust and explainability, governance and accountability, human–AI collaboration, and organizational readiness. These dimensions form the foundation of the proposed assessment model.

The first dimension, **Decision Performance**, evaluates the extent to which AI contributes to improvements in decision speed. For instance, how effective was the AI assisted decision. Examines the ability of AI tools in analysis of operational efficiency and decision consistency. This dimension reflects the performance related to the benefits most frequently identified by participants and observed across the case studies.

The second dimension, **Trust and Explainability**, examines the degree to which AI-generated recommendations are transparent, understandable, and trusted by decision-makers. The findings indicated that explainability and transparency play a critical role in shaping managerial confidence and willingness to rely on AI-supported decisions.

The third dimension, **Governance and Accountability**, focuses on how the monitoring procedures can produce more accountable structures and better compliance in regulations and ethical rules. The findings consistently demonstrated that governance capability supports both responsible AI adoption and decision effectiveness.

The fourth dimension, **Human–AI Collaboration**, evaluates the quality of interaction between AI systems and human decision-makers. This dimension includes human oversight, managerial judgment, decision validation procedures, and the allocation of decision authority between humans and AI systems.

The fifth dimension, **Organizational Readiness**, reflects the extend of organizational readiness in AI adoption, including employee training, AI literacy, leadership commitment, data quality, and continuous learning processes. The findings suggest that these factors significantly influence the successful integration of AI into organizational decision-making.

Taken together, these dimensions provide a holistic perspective on AI-supported decision environments. The AI-DEAI proposes that organizations should evaluate AI success not only in terms of technical performance but also in relation to trust, governance, human oversight, and organizational capability development.

Although the AI-DEAI is conceptual in nature and has not been empirically validated as a quantitative measurement instrument, it is based on the nowadays most common consideration regarding AI successful implementation. Also, provides a foundation for future research and practical assessment. Future studies may further operationalize these dimensions and develop measurement scales capable of evaluating AI decision effectiveness and governance maturity across different organizational contexts.

Furthermore, as Artificial Intelligence becomes more integrated into organizational activities, there may be increasing interest in tools that assess an organization's AI maturity and governance practices. Investors or shareholders, the business partners and potential employees may wish to better understand how organizations use and manage AI technologies. Factors such as AI readiness, governance quality, transparency, and responsible implementation may increasingly be viewed as indicators of organizational reliability, competitiveness, and long-term sustainability. In this context, the AI-DEAI may provide a useful conceptual foundation for the future development of assessment and benchmarking tools that support more informed stakeholder evaluation.

### 5.7.2 Structure of the AI Decision Effectiveness and Assurance Index

The AI Decision Effectiveness and Assurance Index (AI-DEAI) is structured around the five dimensions identified through the empirical findings and incorporated into the AI Decision Governance Framework. These dimensions represent the key organizational factors influencing the effectiveness, trustworthiness, and sustainability of AI-supported decision-making.

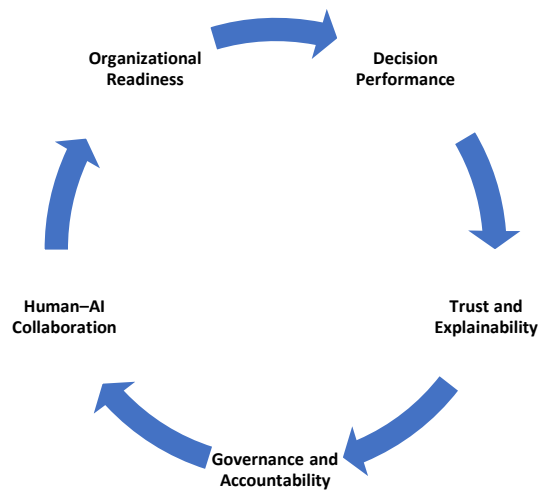
The five dimensions are :

1. **Decision Performance**
2. **Trust and Explainability**
3. **Governance and Accountability**
4. **Human–AI Collaboration**
5. **Organizational Readiness**

Together, these dimensions provide a holistic assessment perspective that extends beyond technical system performance. The AI-DEAI recognizes that successful AI adoption depends not only on technological capability but also on governance structures, managerial trust, human oversight, and organizational preparations.

The conceptual relationship between these dimensions is illustrated below:

### ***AI Decision Effectiveness and Assurance Index***



The model proposes that technological capability alone is insufficient to generate effective decision outcomes. Instead, AI-supported decision effectiveness emerges from the interaction between organizational readiness, governance mechanisms, trust development, and effective collaboration between managers and AI systems. Higher levels of alignment across these dimensions are expected to contribute to stronger decision performance, increased managerial confidence, and more responsible AI adoption.

#### **5.7.3 Dimension 1 Decision Performance Quality (DPQ)**

The Decision Performance Quality (DPQ) dimension evaluates the extent to which AI contributes to improving the overall quality and effectiveness of organizational decision-making. This dimension focuses on the ability of AI-supported systems to enhance analytical capability, improve forecasting accuracy, accelerate decision processes, and support more informed managerial judgments.

The findings of this study indicate that organizations primarily associate AI value with its capacity to process large volumes of information, identify patterns that may not be easily detected by humans, and generate insights that support decision-making under conditions of complexity and uncertainty. Participants frequently reported that AI improves the speed of analysis and provides additional evidence that can strengthen managerial confidence when evaluating alternatives and making decisions.

Importantly, decision performance is not assessed solely in terms of speed. Effective AI-supported decisions should also demonstrate consistency, relevance, and the ability to support organizational objectives. The findings suggest that organizations perceive AI as most valuable when it improves decision quality while complementing human expertise and professional judgment.

Indicative assessment criteria may include:

- Forecasting and prediction accuracy
- Decision speed and responsiveness
- Quality of analytical insights

- Consistency of decision outcomes
- Support for strategic and operational decisions
- Contribution to organizational performance objectives

This dimension reflects the performance-oriented benefits of AI adoption and focuses on how AI enhances decision effectiveness through improved information processing, analytical capability, and evidence-based decision support. As such, it represents a core component of evaluating the value generated by AI-supported decision environments.

#### 5.7.4 Dimension 2 Trust, Transparency, and Explainability (TTE)

This dimension evaluates how much AI-supported decision systems are trusted and understood. Also evaluates how accepted are by managers in decision making. The findings of this study consistently identified trust, transparency, and explainability as critical factors influencing managerial willingness to rely on AI-generated recommendations.

Participants reported greater that they are more confident with AI systems when decision processes were transparent and when the reasoning behind recommendations could be understood and evaluated. Similarly, the COMPAS case study demonstrated how limited explainability and automated decisions can reduce trust and raise concerns regarding accountability and decision legitimacy. These findings suggest that trust is influenced not only by technical performance but also by users' ability to understand how AI systems operate and generate outputs.

Indicative assessment criteria may include:

- Perceived explainability of AI-generated recommendations
- Managerial trust in AI-supported decisions
- Frequency of human overrides or manual interventions
- Consistency of decision confidence
- Perceived transparency of decision processes
- User understanding of AI system capabilities and limitations

The frequency of managers modifying the AI recommendations may provide useful insight into the relationship between trust and reliance on AI systems. While occasional overrides may reflect appropriate human oversight, if managers consistent override the AI decision could indicate concerns regarding trust, explainability, reliability, or system performance.

Overall, this dimension reflects the view that explainability is not only a technical characteristic but also an important organizational factor supporting trust, accountability, and effective human–AI collaboration. The findings suggest that organizations that promote transparency and user understanding are more likely to achieve sustainable and responsible AI adoption.

#### 5.7.4.1 Decision Safety Differential (DSD)

As an extra evaluation tool for trust in AI implementations a complementary indicator could be the Decision Safety Differential (DSD). The indicator could assess whether managers are more protected when they use AI in decision making and facing less risk in contrary with human-only decision processes.

$DSD = \text{Decision-related Risk Incidents (made only by Humans)} - \text{Decision-related Risk Incidents (Human collaborated with AI tools)}$

A positive DSD value indicates that AI-supported decision environments are associated with lower levels of decision-related risk and enhanced decision safety. A value close to zero suggests limited safety improvement, whereas a negative value may indicate that AI implementation introduces additional risks requiring managerial attention and governance intervention.

The DSD is intended as a conceptual governance indicator and may be used alongside the AI Decision Effectiveness and Assurance Index (AI-DEAI) to provide a more comprehensive assessment of both decision performance and decision safety outcomes.

#### 5.7.5 Dimension 3 Governance Accountability (GA)

This dimension evaluates the extent to which organizations have established formal governance structures to support the responsible use of AI in decision-making processes. The findings of this study consistently highlighted governance as a key factor influencing trust, accountability, and the effective integration of AI into organizational decision environments.

Participants reported greater confidence in AI-supported decisions when clear monitoring procedures, accountability mechanisms, and validation processes were in place. Similarly, the case studies demonstrated that governance practices play an important role in determining whether organizations can effectively translate AI capabilities into reliable decision outcomes. These findings suggest that governance maturity influences both decision effectiveness and organizational trust in AI systems.

Indicative assessment criteria may include:

- Model validation procedures
- Auditability and traceability capabilities
- Data governance practices
- Ethical oversight mechanisms
- Regulatory compliance monitoring
- Accountability role clarity
- Decision review and escalation procedures

This dimension reflects the view that governance extends beyond compliance requirements and functions as an important organizational capability supporting responsible AI adoption. The findings suggest that organizations with more mature governance structures are better positioned to manage risks, maintain accountability, and integrate AI into decision-making processes with greater confidence and effectiveness.

Overall, Governance Maturity represents a foundational component of the AI-DEAI model, supporting transparency, trust, human oversight, and long-term organizational readiness for AI adoption.

#### 5.7.6 Dimension 4 Human–AI Collaboration Effectiveness (HACE)

This dimension evaluates the quality of interaction between managers and AI systems within organizational decision environments. The findings of this study consistently demonstrated that AI is most effective when used as a decision support tool that complements managerial expertise rather than replacing human judgment. Participants repeatedly emphasized the importance of human oversight, contextual interpretation, and decision validation when using AI-generated recommendations.

The interviews and case studies suggest that successful AI adoption depends on establishing clear collaboration structures between humans and AI systems. Organizations that define decision responsibilities, validation procedures, and escalation mechanisms appear better positioned to integrate AI into decision-making processes while maintaining accountability and strategic control.

Indicative assessment criteria may include:

- Human–AI co-creation and collaboration level
- Clarity of decision authority allocation
- Maturity of escalation and validation procedures
- Reduction of cognitive workload in decision processes
- User satisfaction with AI-supported collaboration
- Effectiveness of human oversight mechanisms
- Alignment between AI recommendations and managerial judgment

This dimension is grounded in augmented intelligence theory, which views AI as a capability that enhances rather than replaces human decision-making. The findings suggest that the greatest value is achieved when AI contributes analytical capability while managers provide contextual understanding, ethical evaluation, and strategic direction.

Overall, Human–AI Collaboration Effectiveness represents a critical component of the AI-DEAI model. Effective collaboration enables organizations to combine technological intelligence with human expertise, supporting more informed, accountable, and reliable decision-making outcomes.

#### 5.7.7 Dimension 5 Organizational Readiness (OR)

This dimension refers to the extent to which an organization possesses the capabilities, resources, and organizational conditions necessary to successfully adopt and integrate

Artificial Intelligence into managerial decision-making processes. The empirical findings of this study indicate that AI implementation success depends not only on technological sophistication but also on the organization's preparedness to support AI-driven transformation through appropriate leadership, culture, skills, and infrastructure.

This dimension evaluates the organization's ability to create an environment that facilitates the effective adoption and utilization of AI-supported decision systems. Organizations with higher levels of readiness are more likely to achieve successful implementation outcomes, enhance managerial acceptance of AI technologies, and reduce resistance to organizational change. In contrast, organizations with lower readiness levels may face implementation challenges, limited user adoption, and reduced decision effectiveness despite possessing advanced technological capabilities.

The findings further suggest that Organizational Readiness serves as a foundational enabler of AI adoption, supporting the development of governance mechanisms, trust in AI-supported systems, and effective human–AI collaboration. Consequently, this dimension captures the organization's overall preparedness to operationalize AI technologies and sustain long-term AI-driven transformation initiatives.

**Indicative assessment criteria may include:**

- AI literacy and capability in workforce
- Support by Leadership and committed AI strategies
- Organizational culture and emphasis to innovation
- Change adaption capability
- Technological and data infrastructure readiness.

Higher scores indicate a well-organized corporation in terms of AI implementations and a greater capacity to achieve effective, responsible, and sustainable AI-supported decision-making outcomes.

### 5.7.8 Composite Index Structure

The overall AI-DEAI score can be calculated using weighted multi-dimensional aggregation:

Where:

**DPQ = Decision Performance Quality**

**TTE = Trust Transparency and Explainability**

**GA = Governance Accountability**

**HACE = Human AI Collaboration Effectiveness**

**OR = Organizational Readiness**

Weighting coefficients may be adjusted based on industry context, regulatory exposure, and decision criticality level.

### 5.7.9 Theoretical Contribution

The AI-DEAI model contributes to the academic literature by extending existing approaches to the evaluation of AI-supported decision-making beyond purely technical performance considerations. While many evaluation approaches focus primarily on predictive accuracy, efficiency, or system performance, the AI-DEAI incorporates organizational dimensions such as governance, trust, explainability, and human–AI collaboration.

The model brings together insights from decision-making theory, governance research, augmented intelligence, and socio-technical systems theory within a single conceptual assessment framework. By integrating both performance-related and governance-related dimensions, the AI-DEAI provides a broader perspective on how organizations can evaluate the effectiveness and trustworthiness of AI-supported decision environments.

Furthermore, the model contributes to the growing discussion on responsible AI adoption by emphasizing that decision effectiveness depends not only on technological capability but also on governance maturity, managerial trust, and effective human oversight. In this way, the AI-DEAI complements the AI Decision Governance Framework proposed in this study and provides a conceptual foundation for future research seeking to assess AI-supported decision environments across different organizational contexts.

### 5.7.10 Managerial Application

The AI Decision Effectiveness and Assurance Index (AI-DEAI) provide a structured approach that organizations may use to assess AI-supported decision environments from both performance and governance perspectives. Unlike evaluation approaches that focus primarily on technical performance indicators, the AI-DEAI incorporates dimensions related to governance, trust, human–AI collaboration, and decision risk considerations, reflecting the multidimensional nature of AI-supported decision-making.

The model encourages organizations to evaluate AI adoption not only in terms of efficiency and predictive capability but also in relation to accountability, transparency, oversight, and organizational readiness. By adopting a broader assessment perspective, managers can gain a more comprehensive understanding of the factors that influence the effectiveness and trustworthiness of AI-supported decisions.

The AI-DEAI may also assist organizations in identifying governance gaps, strengthening oversight mechanisms, and supporting continuous improvement initiatives. The dimensions incorporated within the model provide a practical structure for reviewing decision processes, monitoring AI integration progress, and evaluating the balance between technological capability and organizational control.

From a managerial perspective, the model highlights the importance of aligning AI implementation with governance practices, employee capabilities, and human oversight mechanisms. This integrated approach supports responsible AI adoption while helping organizations improve decision quality, strengthen accountability, and enhance confidence in AI-supported decision environments.

Although the AI-DEAI is conceptual in nature, it offers a practical foundation that organizations and researchers may further develop and adapt to different industry contexts, decision environments, and governance requirements.

### 5.7.11 Research Implications

The AI Decision Effectiveness and Assurance Index (AI-DEAI) provide several opportunities for future research. As the model is conceptual in nature, future studies may further operationalize its dimensions and develop measurement scales capable of assessing AI-supported decision environments across different organizational contexts.

Future research could empirically examine the relationships between the dimensions of the model through quantitative methods, larger samples, and cross-industry comparisons. Such studies may contribute to the validation and refinement of the proposed framework while providing additional evidence regarding the interaction between governance maturity, trust, human–AI collaboration, and decision effectiveness.

Future research may also provide valuable insights into how governance practices, organizational trust, and AI adoption evolve over time. Examining these dynamics could improve understanding of how organizations develop AI capabilities and how governance maturity influences long-term decision outcomes.

In addition, future studies may explore the applicability of the AI-DEAI across different industries, organizational sizes, and regulatory environments. This could support the development of sector-specific governance maturity benchmarks and contribute to the advancement of responsible AI adoption practices.

Overall, the AI-DEAI provides a conceptual foundation that future research may further refine, validate, and adapt to support the evaluation of AI-supported decision-making in increasingly complex organizational environments.

## 5.8 Final Conclusions

This study examined the impact of Artificial Intelligence on managerial decision-making by exploring the opportunities, the challenges, and governance implications associated with AI-supported decision environments. The findings indicate that Artificial Intelligence has the potential to enhance decision quality and offer better analytical capability. Organizational responsiveness is very important particularly in contexts characterized by high complexity and uncertainty or large volumes of data. However, the research also suggests that technological capability alone is insufficient to ensure successful AI integration. Effective adoption appears to depend on the alignment between technological systems, governance practices, managerial trust, and human–AI collaboration.

A central conclusion of the study is that Artificial Intelligence functions primarily as a decision augmentation mechanism rather than a decision replacement technology. Across the interviews and case studies, hybrid human and AI decision models emerged as the most effective organizational approach. If a company can combine algorithmic analytical capability with human contextual understanding will have better results. These findings reinforce the importance of maintaining human oversight and clearly defined decision authority structures within AI-enabled organizations.

The research further highlights the importance of governance maturity in supporting effective AI adoption. Organizations with more developed governance structures appeared to demonstrate higher levels of managerial trust and offer more accountable mechanisms, and more effective integration of AI-generated insights into decision processes. These findings suggest that governance should be viewed not only as a risk management function but also as an organizational capability that supports responsible and sustainable AI adoption.

Based on the empirical findings, the study proposed an AI Decision Governance Framework designed to support organizations in accessing both effective decision outcomes and responsible AI implementation. The framework integrates the key dimensions identified throughout the research, including decision performance, trust and explainability, governance and accountability, human–AI collaboration, and organizational readiness.

In addition, the study introduced the AI Decision Effectiveness and Assurance Index (AI-DEAI) as a conceptual assessment model for evaluating AI-supported decision environments. The AI-DEAI extends traditional performance-oriented perspectives by incorporating governance, trust, decision safety, and human–AI collaboration considerations into a multidimensional evaluation approach.

From a theoretical perspective, the study contributes to the literature by integrating insights from decision-making theory, socio-technical systems theory, governance research, and intelligence perspectives into a united framework for understanding AI-supported managerial decision-making. From a managerial perspective, the findings provide practical guidance for organizations seeking to implement AI in a more effective and contemporary way.

Overall, the research suggests that the future of managerial decision-making lies not only in not replacing human judgment by Artificial Intelligence, but in the development of collaboration decision environments where human expertise and algorithmic can operate together. Organizations that successfully integrate Artificial Intelligence into their decision-making processes, while maintaining effective governance and human oversight, they will play a significant role in shaping the future society.

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### Δήλωση Συγγραφέα

Δηλώνω ρητά ότι, σύμφωνα με το άρθρο 8 του Ν. 1599/1986, η παρούσα εργασία αποτελεί αποκλειστικά προϊόν προσωπικής εργασίας και δεν προσβάλλει κάθε μορφής δικαιώματα διανοητικής ιδιοκτησίας, προσωπικότητας και προσωπικών δεδομένων τρίτων. Δεν περιέχει έργα ή εισφορές τρίτων για τα οποία απαιτείται άδεια των δημιουργών ή δικαιούχων και δεν είναι προϊόν μερικής ή ολικής αντιγραφής. Οι πηγές που χρησιμοποιήθηκαν περιορίζονται στις βιβλιογραφικές αναφορές και πληρούν τους κανόνες της επιστημονικής παράθεσης.

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