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The Role of AI and Blockchain in Project Management: How Emerging Technologies Are Redefining Project-Based Organizations

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Introduction

Artificial intelligence is one of the most powerful transformative factors in project management today, constantly changing how organizations lead projects, allocate resources, and compose teams. Especially for Project-Based Organizations operating within flexible and temporary structures, it seems like one of the hardest-hit areas regarding AI-driven innovation. The adoption of AI tools in these contexts can significantly impact decision-making efficiency, risk assessment, and strategic planning, while also introducing challenges in maintaining a balanced relationship between automation and human leadership (Shamim, 2024).

The objective of this thesis is to understand "How AI is reshaping leadership in project management within PBOs". More precisely, it probes into how AI-driven decision-making processes influence managerial roles, competencies, and team coordination, outlining the opportunities that arise, together with organizational resistances to integrating AI into leadership functions (Paudel, R., 2024). The study further looks at Blockchain technology, mainly how it helps in enhancing transparency and accountability during project execution (Markopoulos et al., 2020).

The research uses quantitative methods to study this question through surveys of project managers and HR managers and team members in Project Based Organizations (PBOs). The research investigates three main aspects which include AI adoption in organizational processes and decision-making and how AI transforms managerial competencies and the obstacles that emerge from AI implementation in leadership roles. The research aims to create a comprehensive understanding through data analysis which demonstrates how organizational design transforms during the AI era while identifying both positive aspects and essential challenges of AI implementation in project-based organizations. The research investigates AI's influence on human leadership through an examination of whether AI operates as a decision support tool or if it alters fundamental project management responsibilities.

Chapter 1 - Literature Review

Artificial Intelligence transforms project management by enabling data-based choices for resource allocation and it reshapes team communication dynamics.

Project-Based Organizations (PBOs) show the most vulnerability to AI transformation because they have short-term operations and flexible systems and require specialized knowledge for their work. These organizations operate in fast-paced and uncertain environments, where the absence of long-term routines and permanent teams complicates managerial decision-making, team coordination, and knowledge retention. AI systems in PBOs create an excellent environment to analyze how artificial intelligence supports both strategic and operational leadership activities. Research indicates that AI systems which include predictive analytics and intelligent scheduling and machine learning models help organizations make better decisions while reducing risks and optimizing resource management (Hobday, 2000; Söderlund, 2004). AI functions as an organizational control mechanism that addresses the standard vulnerabilities which affect PBOs, particularly their limited ability to institutionalize and transfer knowledge across projects. Knowledge tends to remain siloed within temporary teams and is often lost when projects conclude. AI-powered knowledge management platforms can automatically store, categorize, and retrieve organizational insights, enabling continuity across project cycles and promoting organizational learning (Bourouni, Noori & Jafari, 2014).

AI enhances organizational agility and innovation by equipping leaders with tools capable of processing large datasets, identifying patterns, and generating real-time recommendations. In project environments where priorities shift rapidly and decision windows are narrow, AI can assist in making more objective, data-informed judgments that transcend human bias and cognitive overload (Shenhar & Dvir, 2007). Workforce analytics powered by AI can even dynamically match competencies to project requirements, thus avoiding skill mismatch and offering the optimal team design. Such systems find great applications in those industries where PBOs are typical—i.e., construction, IT, consulting, and engineering—where a number of projects must be juggling concurrently within resource constraints and with tight timelines.

Another critical area where AI holds promise is in team communication and coordination. PBOs maintain a distinct communication structure which allows their experts to exchange information freely across different functional areas because of their diverse skill sets. AI systems function as coordination tools which boost communication efficiency through real-time automatic information sharing and predictive breakdown detection. Machine learning algorithms enable teams spread across different locations to handle language differences and create better pathways for team member knowledge sharing. The project execution benefits from these competencies which also modify leadership dynamics by moving project manager authority from direct control to facilitation and orchestration and technology stewardship.

Research on AI applications in PBOs helps scientists understand how digital transformation affects leadership systems and governance frameworks. AI technology provides significant operational advantages through automation yet generates critical challenges regarding decision autonomy and algorithmic bias and ethical leadership (Bourouni, Noori & Jafari, 2014). The main challenge in AI tool implementation stems from their ability to operate technically while understanding project environments through handling unpredictable and changing project work. The research must study how human decision-making interacts with algorithmic recommendations because this connection shapes leadership roles and team trust and organizational design. The research investigates how AI technology affects PBO project management leadership practices through an analytical study. The study investigates how AI decision systems affect leadership abilities and team coordination and management positions while pinpointing organizational challenges and strategic opportunities that result from this change (Paudel, 2024).

The research investigates how Blockchain technology can boost transparency and accountability in AI-based project governance systems to create additional digital innovations for project organizations (Markopoulos et al., 2020). The research design uses a quantitative approach with a structured questionnaire to collect data from project managers and HR professionals and team members in PBOs. The research focuses on core dimensions such as AI adoption, competency transformation, and trust in AI-enhanced leadership. Through empirical analysis, the study contributes to a broader understanding of how organizational design is evolving in the AI era, and whether artificial intelligence remains a support system for leadership—or whether it is progressively redefining the very foundations of project leadership itself (Shenhar & Dvir, 2007; Söderlund, 2004).

1.1 Artificial Intelligence: Definition, Challenges and Applications

1.1.1 Definition of Artificial Intelligence

The concept of Artificial Intelligence (AI) holds significant importance in computer science and business management while experts actively study and develop it. The academic literature contains various definitions of AI but researchers have not established a unified definition. The academic community defines AI through various perspectives which span from engineering to philosophical and cognitive approaches. One of the very first attempts to characterize Artificial

Intelligence (AI) is documented in Alan Turing (1950) who, in his now foundational paper Computing Machinery and Intelligence, suggested the so-called Turing Test as an experiment for AI. Following Turing, an intelligent system is one that is capable of simulating human action to the degree of deceiving an observer to such an extent that it will be indistinguishable from a human respondent (Russell & Norvig, 2016). Such a train of thought has had a permanent influence on the post-Issue discussion regarding AI centered around the concept of computational intelligence and autonomous learning.
The second definition was set in 1956 by John McCarthy; he used the term "Artificial Intelligence" in the Dartmouth Summer Research Project on Artificial Intelligence. McCarthy, et al. (2006) have also presented a definition for AI as "the science and engineering of making intelligent machines, especially computer programs that have the ability to solve problems that, if solved by humans, would require intelligence.". This view asks for the engineering aspect of AI, as opposed to the study of human cognition and focusing on building systems that learn, plan, and adapt to external inputs.

From a technological point of view, Russell and Norvig (2016) propose a classification of artificial intelligences, dividing them into four main categories:

- Systems that think like humans (e.g. artificial neural networks that simulate the functioning of the brain);
- Systems that act like humans (e.g. chatbots and virtual assistants);
- Systems that think rationally (e.g. logic-based decision-making algorithms);
- Systems that act rationally (e.g. autonomous agents in problem-solving contexts).

This difference is essential, as it emphasizes the twofold aim of replicating and maximizing human intelligence using sophisticated technological devices.
In the past decades, the term AI has been broadened from the computational process, to also include its social and ethical dimensions of being utilized. Yudkowsky (2008) distinguishes between weak AI (Narrow AI), i.e. specialized programs that can solve particular problems (e.g. search engines, voice assistants), and strong AI (General AI), which is theoretically able to fully emulate human intellectual capabilities. While the former is an established fact, the latter remains an area of theoretical study, with consequences ranging from the philosophy of mind to the regulation of AI.

A further contribution to the definition of artificial intelligence comes from studies on the economic and employment impact. AI is not just a technological tool, but a real catalyst for social transformation, capable of redefining the dynamics of the labour market and human relationships (Shen & Zhang, 2024). This suggests that a contemporary definition of AI should include not only technical aspects, but also economic, ethical and psychological variables.

If AI was initially conceived as a simple automation tool, today it represents a central element in technological and organizational innovation processes, with an increasingly pervasive impact on corporate structures and social dynamics.

1.1.2 Evolution of AI and main historical milestones

Artificial intelligence (AI) experienced various epochs of evolutionary progression from initial theoretic ideas towards its current position as a widespread technology across disciplines. The process of its growth has been marred by such milestone events, which document progress from basic computational mathematics to complex systems capable of learning, development, and autonomous decision-making.

AI theories were developed in the 1940s and 1950s when cybernetics emerged and the initial attempts were made to define intelligence computationally. Alan Turing (1950) led the early stage of development as a prominent personality who introduced the Turing Test for evaluating machines' ability to mimic human action (Russell & Norvig, 2016). It was also the year when computer architecture concepts that continue to define computer design now were developed by mathematician John von Neumann and established groundwork for the future development of AI (McCarthy et al., 2006).

1956 was the key year when work on artificial intelligence began at the Dartmouth Summer Research Project under the leadership of John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon. The term “Artificial Intelligence” was used in this conference when scientists developed a new field of study (McCarthy et al., 2006). The first computer programs for artificial intelligence were developed in the 1950s and 1960s. e.g., Newell and Simon's Logic Theorist (1956) seem to be the first AI program to prove mathematical theorems while the General Problem Solver (GPS) (1957) codified problem-solving.

During the 1970s, AI slowed down in a phenomenon known as the “AI Winter” due to dwindling expectations and lacking enough computing power to produce innovative systems. But AI was once again brought back in the 1980s by the bulk deployment of expert systems for computer programs mimicking human thought in a field of expertise not yet completely comprehensible to humans, for example, Digital Equipment Corporation's XCON system (Russell & Norvig, 2016). Artificial neural networks were applied at the same time, based on the human brain model, and the backpropagation algorithm by Rumelhart, Hinton, and Williams (1986), allowing the grand leap of machine learning (Yudkowsky, 2008).

The entry of big data and machine learning during the early 2000s was the turning point that AI had been waiting for. With improvements in computing power and availability of large amounts of data, deep learning algorithms began producing results that were unprecedented. The 2012 convolutional neural network AlexNet became the first model to outperform all previous image recognition systems according to Russell & Norvig (2016).

AI technology has experienced rapid growth throughout the last ten years as it entered multiple business domains including healthcare and banking and project administration. The platform capabilities of IBM Watson show how AI technology helps doctors make improved medical decisions while GPT-4 demonstrates that machines can now produce both creative and analytical work. AI technology development at a rapid pace has produced various ethical dilemmas and employment-related difficulties. Shen & Zhang (2024) analyze how AI transforms the job market by opening new opportunities yet generating substantial challenges for human job replacement in particular industries.

1.1.3 Ethical and organizational challenges in AI adoption

Business operations that use Artificial Intelligence systems generate various organizational and ethical problems which organizations need to address effectively to achieve efficient and responsible AI deployment. The three main areas of focus include privacy protection and data security as well as algorithmic decision-making transparency and organizational job redesign and resistance to change.

The most important challenge from an ethical perspective is privacy. AI depends on processing huge amounts of data, at times sensitive, which may at times include personal data. The risk of information misuse becomes more likely when proper regulations and sufficient security protocols are not in place (Brundage, 2018). Organizations need to establish control mechanisms for proper data processing that follows current regulations including the GDPR in the European Union.

The other essential element to evaluate is transparency. The output of machine learning and deep learning algorithms remains difficult. The lack of transparency in algorithmic decision

systems leads to significant accountability problems because these systems generate dangerous outcomes in critical areas including medical treatment and judicial processes.
The implementation of AI systems to preserve existing biases in training data generates an ethical problem which we identify as algorithmic bias. This process has been the target of analysis across a variety of fields, for example in staff hiring, with the danger of discrimination on the grounds of gender, ethnicity or class (Jobin et al.,2019).
To avoid this attack, more fair algorithms must be designed and auditing processes performed to identify and correct the biases.
On the corporate front, business adoption of AI is one of the main challenges. Among the biggest challenges is change resistance. Most employees fear that AI will replace their jobs, acting as a substitute technology rather than an integrative one, and leading to unemployment. However, it has been researched that AI, rather than displacing job roles, has the effect of altering them, requiring new competencies and training (Davenport & Ronanki, 2018), thus challenging current employees to redesign their competencies and become integrated into new organizational forms.
The second is technological integration and management of AI-based systems. Businesses have to transform their organizations and procedures to accommodate new technologies, which involves significant investment in infrastructure and human resources training. Moreover, the lack of an established and standard regulatory system on an international level is also an obstacle to the use of AI, which means that a structure of uncertainty for how and how much to utilize this instrument inside companies remains. (Kaplan & Haenlein, 2019)
Skills and human capital management is also a success factor for the adoption of this technology. Companies must invest in training programs in order to allow employees to successfully interact with new technologies in an effective and safe way. The program provides students with the ability to learn technical skills and analytical abilities and decision-making competencies needed for work environments that use automation and data-intensive systems (Davenport & Kirby, 2016).

1.1.4 AI Applications in Business Organizations

Artificial intelligence has transformed business operations through enhanced decision-making and process optimization which enables organizations to find new growth opportunities while reshaping work organization systems across multiple business sectors.

The human resources sector shows the most evident impact from AI technology implementation. Modern computer programs with machine learning capabilities enable automated resume processing systems to evaluate candidates for faster recruitment while achieving better hiring accuracy. People analytics software enables organizations to detect employee performance patterns and predict staff turnover so they can implement preventive strategies to boost worker health and productivity (Russell & Norvig, 2016). The tools deliver major competitive advantages but create ethical dilemmas which threaten to compromise the transparent operation of machine-based decision systems (Müller, 2016).

The implementation of artificial intelligence in business operations enables better decision-making and process optimization which leads organizations to find new growth opportunities while transforming their work organization systems across different business sectors.

The financial industry underwent a complete transformation because of artificial intelligence which now handles data analysis and risk management operations differently. Predictive models detect irregularities in transaction patterns to stop fraud while machine learning models evaluate credit risk to enhance investment operations (Bostrom & Müller, 2016). The financial advisory platform robo-advisors operates through AI technology to deliver personalized services which lower the expenses of wealth management. The tools enhance financial service delivery yet their complete business adoption remains limited because they lack a system for error responsibility assignment.

AI technology implementation in supply chain and logistics operations results in optimized operational processes. The implementation of predictive analytics by organizations produces exact demand forecasts which enables them to reduce waste while achieving better operational results through automated warehouse systems. The leading companies in the industry use smart robots and autonomous vehicles to boost their storage and delivery operations according to Russell (2016) which results in faster product delivery with improved accuracy. The system operates with reduced costs while maintaining flexibility to adapt to market changes. The strategic process development capabilities of AI technology lead to improved operational performance. Organizations employ sophisticated data analysis tools to support their managerial decision-making processes. The system analyzes extensive consumer preference data to create personalized product and service offerings. The tools help businesses achieve market leadership through their ability to respond quickly to market fluctuations (Müller & Bostrom, 2016). Organizations need to establish a balanced approach that unites technological strength with human oversight to achieve successful AI implementation through transparent and ethical information management. Business organizations are adopting AI applications at a rapid pace to transform their operational systems and decision-making frameworks. The platform helps organizations achieve process optimization and innovation through advanced tools but these capabilities create new management difficulties that need proper governance and strategic oversight.

1.2 Project-based Organizations: Features, Benefits and Rationale for the Study

1.2.1 Characteristics of Project-Based Organizations (PBOs)

Project-based organizations (PBOs) operate as an organizational framework which uses projects as the fundamental production units for innovation and value creation. Project-based organizations (PBOs) function differently than matrix or functional organizations because they create flexible project-based systems to unite diverse competencies for reaching organizational objectives (Hobday, 2000). This organizational structure is common in highly complex industries with high levels of innovation and product/service customization, such as aerospace, construction, IT and film-making (Lundin and Söderholm, 1995).

PBOs possess structural flexibility as their main advantage which enables them to quickly respond to unstable market conditions and shifting customer requirements. Each project is a semi-autonomous organization, drawing on knowledge and resources to address specific challenges. This kind of arrangement is reactive and flexible, making PBOs particularly well suited to deal with complex products and systems (CoPS), high-value, large, and technologically advanced solutions requiring intense coordination across multiple stakeholders (Hobday, 2000). The project-based approach makes dynamic team and resource restructuring easier, allowing the skills to be matched up against changing project requirements instead of being restricted by static departmental boundaries.

Another distinguishing feature is the short-term and activity-oriented character of PBOs, as conceptualized by the 4T model of Lundin and Söderholm (1995), with four main dimensions: time, activity, team, and transition. The limited duration of projects requires a strong focus on achieving objectives within certain time frames, which distinguishes PBOs from permanent organizations that operate continuously. Activity specificity ensures that the labour is oriented toward generating tangible outcomes, and team composition gets reorganized frequently to accommodate skills needs for differing project stages. Finally, transition stage forms a closure of a project and management of knowledge, expertise, and workforce to new ventures, establishing an ethos of learning and knowledge propagation.

Governance-wise, PBOs reflect a decentralized model of decision-making, in which project managers have substantial autonomy and control of resources, personnel, and strategic direction (Hobday, 2000). Unlike functional organizations, where power resides in hierarchical management, or matrix organizations, where dual authority can lead to conflict, PBOs vest power in project managers to be entrepreneurial leaders responsible for the success of the project (Shenhar and Dvir, 2007). This management flexibility enhances flexibility and innovation, enabling project teams to test out innovative solutions and implement strategic change rapidly.

Knowledge management in PBOs holds promise and threat. On the one hand, the tight coupling of multi-functional knowledge among project teams facilitates the development of deep, problem-specific knowledge. Conversely, the transitory nature of projects presents challenges to organizational learning accumulation and transfer (Söderlund, 2004). The lack of permanent storage facilities for knowledge leads to knowledge fragmentation because essential pieces of wisdom become isolated within specific project groups instead of being integrated across the organization. The establishment of Communities of Practice (CoP) and Knowledge Networks (KN) and virtual repositories serves as a response to create knowledge transfer channels between projects (Bourouni, Noori, & Jafari, 2014).

The two primary organizational structures of PBOs differ from each other because they follow either a pure project-based design or a hybrid model which combines functional stability with project-oriented adaptability (Hobday, 2000). Pure PBOs perform their activities through direct project assignments but hybrid structures maintain permanent R&D and HR and finance functions to support both strategic planning and operational stability. The method enables PBOs to address their main limitation which makes it challenging to achieve both large-scale efficiency and sustained organizational learning.

The inherent nature of PBOs allows them to handle complex and uncertain operational environments. The Diamond Model developed by Shenhar & Dvir (2007) shows that project requirements vary based on novelty and technology and complexity and pace which demands adaptive management approaches. The core strength of PBOs emerges from their ability to excel in situations that demand ongoing innovation alongside fast problem-solving and team-based collaboration. The organization's capacity to build specialized teams for particular tasks enables them to handle complex situations while delivering maximum value.

1.2.2 Differences Between Project-Based Organizations and Other Organizational Structures

Project-based organizations (PBOs) represent a new organizational approach which differs from traditional structures including functional and divisional and matrix systems through their governance models and flexible operations and knowledge management systems. The evaluation of PBO strengths and weaknesses requires understanding their organizational differences from other business structures (Hobday, 2000).

The functional organizational structure represents the oldest organizational design which groups activities through specialist departments that handle operations and finance and marketing and research and development. The organizational structure provides employees with domain expertise and scale advantages and employee career stability (Söderlund, 2004). The functional organizational structure faces challenges in market adaptation because its bureaucratic systems and hierarchical decision-making processes create coordination difficulties.

PBOs base their operations on flexible team structures which integrate multiple functions. The project-based organizational structure of PBOs uses short-term teams that bring in specialists from different fields when needed. The organizational structure enables companies to deliver fast customer responses and customized solutions and innovative products when standardization becomes impossible (Hobday, 2000). The lack of a functional structure creates potential knowledge retention problems because project-based expertise remains tied to individual projects rather than being embedded within the organization.

The main difference between functional organizations and PBOs exists in their optimization for stability and efficiency versus flexibility and innovation. The manufacturing sector and standardized output processes benefit from functional organizations yet PBOs excel in complex projects with high uncertainty and distinctive requirements such as aerospace and IT and construction (Lundin and Söderholm, 1995).

Organizations use divisional structures to create semi-autonomous units based on product lines and geographic regions and customer segments. The divisional structure provides market responsiveness through independent decision-making units which have their own resources (Shenhar and Dvir, 2007).

The divisional structure provides business units with flexibility but maintains organizational stability through hierarchical structures which direct long-term strategic planning. The divisional organizational structure faces three main challenges which include duplicate resource allocation between units and weak unit coordination and information protection (Hobday, 2000).

PBOs operate without fixed divisions because they form temporary teams for each project. The method enables maximum resource flexibility because experts join different projects based on organizational requirements. The approach enhances both organizational agility and creative output but leads to difficulties with resource management and strategic planning stability. The project-based organization structure leads to team disbandment after project completion which results in worker career development challenges and organizational instability (Bourouni, Noori, & Jafari, 2014).

The primary distinction between these organizational forms stems from their focus on operational management and expansion within divisional structures versus project delivery in PBOs. The main distinction between these organizational forms stems from their objectives because divisional structures focus on sustaining business operations and expansion but PBOs concentrate on delivering specific high-value projects. The selection between divisional forms and PBOs depends on whether the organization operates in a stable environment that requires divisional forms or a dynamic innovative environment that needs PBOs.

The matrix design combines functional and project-based advantages through dual reporting relationships between employees who work under both functional and project managers (Hobday, 2000). The design enables organizations to distribute resources effectively between projects and maintain specialized skills while supporting project innovation through skill sharing.

The matrix organizational structure creates complex decision-making processes which lead to potential conflicts between project and functional team priorities. The employees face dual reporting challenges because they must answer to their functional manager and project manager which creates role confusion and conflicting organizational commitments (Shenhar & Dvir, 2007). The dual management structure leads to power struggles and inefficient resource management and delayed responses when decision-making processes lack proper coordination (Söderlund, 2004).

Project-based organizations (PBOs) resolve matrix design problems by giving project managers complete control over resource management and decision-making and implementation strategy. The project-focused structure enables fast decision-making and goal achievement but results in lost operational stability and increased costs (Hobday, 2000).

Matrix structures fail to handle complex and changing projects effectively. The matrix organizational structure works well for companies needing stable operations and project-based innovation yet it fails to support fast project adaptation and complete project control. PBOs function best in industries with high project risks and customized requirements because they enable effective cross-functional coordination and continuous project reorganization (Bourouni, Noori, & Jafari, 2014).

Since there are always trade-offs involved in each organizational form, most companies are resorting to hybrids, such as the "Project-Led Organization," which offers flexibility based on projects and functional stability (Hobday, 2000). Here, some of the main functions (e.g., R&D, finance, human resources) are stable, but projects are highly autonomous. This reduces inefficiencies of stand-alone PBOs by retaining knowledge storage and economies of scale, as well as the capacity to adjust as required for effective dynamic project completion.

Hybrid types overcome shortcomings of traditional and PBO paradigms in the sense that they:

- Retain organizational knowledge by maintaining functional units over time.
- Provide career permanence for staff while retaining jobs project-based.
- The system should enhance the way different types of projects and long-term goals work together.

The implementation of hybrid structures minimizes certain PBO traps yet these systems must navigate through robust governance frameworks that support both operational stability and project speed (Shenhar and Dvir, 2007)

1.2.3 Benefits and limitations of PBOs in the managerial context

Business organizations use the project-based organization (PBO) structure as their primary framework to manage domains that need innovative solutions and customized complex solutions. The PBO structure provides distinct managerial advantages through its design which enables flexibility and unites different departments and integrates organizational knowledge.

The organization's strong points generate three primary structural issues which stem from resource allocation problems and knowledge preservation difficulties and unstable long-term strategic direction. Managers who work with the PBO model need to grasp its fundamental limitations because they must accept its core constraints (Hobday, 2000; Söderlund, 2004).

One of the most robust PBO strengths is their structural adaptability, allowing organizations to act quickly to changing market demands and technological advances (Hobday, 2000). In functional or matrix organizations, with hierarchical decision making, it requires time for them to respond to external change. PBOs, however, possess decentralized decision-making power that provides high autonomy to project managers. This produces faster decision making, ongoing problem solving, and more responsive resource allocation (Shenhar and Dvir, 2007).

In rapidly changing and competitive settings, such as the technology, construction, and entertainment industries, this adaptability is a major differentiator. By structuring operations around short-term projects, PBOs can rapidly change strategies without being encumbered by bureaucratic processes (Lundin and Söderholm, 1995).

PBOs enable innovation through cross-functional team collaboration which represents one of their main advantages. The traditional functional organizational structure leads to departmental silos which prevent expertise and knowledge from flowing between teams. The project-based organizational structure of PBOs unites teams with diverse expertise that matches the needs of each project (Bourouni, Noori, & Jafari, 2014).

The flexible organizational design enables teams to exchange tacit knowledge which leads to better learning outcomes and enhanced problem-solving capabilities. The project-based structure of PBOs supports R&D-intensive industries because it enables continuous learning and experimentation (Hobday, 2000).

PBOs direct their work toward delivering customer needs because each project defines its objectives through particular results and stakeholder requirements (Söderlund, 2004). The project outcomes undergo specific changes to meet customer requirements in this approach.

Construction and software development projects within PBOs enable continuous customer feedback integration which leads to market-oriented result optimization (Shenhar and Dvir, 2007). The process-based structure of functional organizations fails to support individualized customer requirements because their standardized procedures remain inflexible.

Each project within a PBO operates independently with defined targets and financial limits and time constraints which creates stronger accountability than traditional organizational systems. The project level provides clear success criteria and enables straightforward identification of inefficiencies while maximizing resource utilization according to Hobday (2000).

As compared to matrix organizations, where employees have difficulty managing competing priorities among functional departments and project teams, PBO employees focus exclusively on specific project goals, leading to increased motivation and performance clarity (Bourouni, Noori, & Jafari, 2014).

The largest shortcoming of PBOs is their inability to retain and institutionalize knowledge. Since project teams are disbanded after the project has been finished, useful knowledge does not get passed on to future projects (Söderlund, 2004).

Unlike functional structures, where employees develop in-depth knowledge in a stagnant domain, PBOs risk losing intellectual capital due to high employee turnover and the temporary character of postings (Hobday, 2000). The solutions of Communities of Practice (CoP), Knowledge Networks (KN), and web-based repositories of knowledge are normally adopted in order to counter this issue, but these come at a high price and entail cultural change (Bourouni, Noori & Jafari, 2014).

Another structural limitation of PBOs is their decentralized resource allocation process. Unlike functional organizations, which have stable groups and long-term workforce planning, PBOs must frequently reallocate human and financial resources across projects.

This creates the following challenges:

- Unpredictable career growth: Employees are constantly switching projects with minimal opportunity for long-term development.
- Overuse of skilled expertise: Experts can be kept waiting between projects, reducing organizational effectiveness (Shenhar & Dvir, 2007).
- Competition among limited personnel: Multiple projects may require the same expertise, resulting in internal conflicts over resource allocation (Hobday, 2000).

To counteract these factors, hybrid approaches such as the "Project-Led Organization" are employed by certain organizations, in which core functional teams are kept and project managers are empowered (Hobday, 2000).

Since PBOs emphasize project success at the individual level, there is no long-term corporate business goal alignment. Autonomous projects are typical, and they may result in fragmented efforts and inefficiencies for the corporation (Söderlund, 2004).

Functional and divisional structures guarantee long-term continuity and stability by ensuring that innovation efforts build up and are aligned with corporate strategy (Hobday, 2000).

Without centralized control, PBOs cannot:

- Standardize best practices across projects
- Create a unified corporate culture
- Maintain consistent branding and client relationships

The high administrative costs of PBOs stem from their need to establish and dissolve project teams repeatedly. The process of starting new projects demands additional administrative work

because organizations must develop new management systems and hire staff and adjust their resource allocation which results in higher operational complexity (Shenhar & Dvir, 2007).
The need for distinct leadership and governing systems and support structures for each project leads to duplicated administrative work which makes centralized organizational structures potentially more cost-efficient (Hobday, 2000).

1.3 The Role of AI in Project Management: Measuring its Impact on Leadership

1.3.1 AI in Project Management: Automation and Optimization of Resources

The introduction of Artificial Intelligence (AI) in Project Management has been one of the significant achievements in project management methodologies development, offering advanced tools for resource automation and optimization. Project management has always been based on systematic procedures that require thoughtful planning, constant monitoring and effective management of human and material resources. The project's increasing complexity together with expanding data volumes requires advanced tools for project managers to make essential decisions. The system demonstrates AI's transformative capabilities through its ability to execute autonomous routine operations and identify security risks and optimize resource allocation in unpredictable environments.
The main function of AI in Project Management involves process automation which helps organizations decrease employee workloads and minimize human errors that generate operational inefficiencies. AI software performs automated data processing and generates complex reports and predicts project development paths.
The research conducted by Dam demonstrates that AI systems outperform traditional methods in agile project management by delivering superior product backlog management and sprint planning and task execution tracking precision. 2018. The analysis of historical project data through machine learning algorithms produces time and resource requirements for specific project phases which helps prevent delays and unexpected events.
AI support systems help teams track their work activities which leads to better task distribution and improved project team performance. AI functions as a fundamental resource optimization tool because it helps organizations improve their management of personnel and material resources in project operations. The implementation of artificial intelligence through neural networks and genetic algorithms allows for precise work requirement prediction and cost

estimation in projects according to Davahli (2024). AI-based predictive analytics enables project managers to detect future project obstacles and operational problems which allows them to distribute resources effectively at the right time. The main advantage of these technologies includes project risk management because AI systems can process large datasets to detect hidden patterns which enable them to predict upcoming issues.

AI technology shows substantial advancement because it enables organizations to handle stakeholders and maintain communication systems. The implementation of AI chatbots in projects has transformed stakeholder communication through their ability to deliver immediate personalized responses according to Joshi (2024). The current NLP breakthroughs in chatbots enable them to automatically answer basic questions and project status updates and collect immediate feedback from users. The system enables quick communication which results in better stakeholder satisfaction and it reduces response times and eliminates communication mistakes that lead to misinterpretations. Organizations experience multiple challenges when transitioning to AI project management systems despite obtaining various advantages from their implementation. The main challenge in AI model implementation for project instances involves creating adaptable models to generate reliable predictive models and operational optimization plans. The management of projects through AI remains limited in certain areas such as communications and procurement management according to Davahli (2024). AI technologies hold the potential to transform project management yet their successful implementation depends on technological advancements and project managers' ability to adopt these systems into regular operations.

1.3.2 The Impact of AI on Leaders' Skills and Roles

The implementation of Artificial Intelligence (AI) in project management has created two major effects that transform operational workflows and force project managers to acquire fresh leadership competencies. With automation of many conventional leader activities, a new leadership model is needed, in which analytical ability, data handling and human-computer collaboration are competencies. The project manager used to focus on monitoring tasks and resource distribution and problem resolution but now needs to learn new skills to maximize AI benefits through predictive algorithm understanding and data analysis and AI-based decision tool operation (Davahli, 2024).

AI-supported decision-making systems allow leaders to leverage this fundamental transformation for better project planning and management operations. AI systems analyze large datasets to generate comprehensive insights about team performance and project timelines and risk elements which enables project managers to make timely decisions with high quality results (Dam et al., 2018). AI systems will not replace human leaders but they will transform their work into strategic information management and essential interpretation of algorithmic data.

Project management success depends on the ability to combine human instinct with analytical data provided by AI systems.

Project leaders must now acquire new skills because of the changing requirements in their work. Project leaders need to maintain their existing communication and team management and conflict resolution abilities yet they must also develop new technological competencies. According to Joshi (2024), the increasing use of AI chatbots in stakeholder management is altering the way leaders engage in communication with different stakeholders in the project. While previous communication required a lot of human interaction, leaders today must be able to manage communication automation tools, monitor the operation of chatbots and intervene where greater relational sensitivity is required. The process requires NLP application expertise development and AI-stakeholder research to make technology enhance interaction quality instead of diminishing it.

The implementation of AI technology in project management has reshaped organizational design and leadership operations by moving from traditional vertical leadership to distributed collaborative management systems. AI provides project teams with immediate data access which enables them to function autonomously during decision-making processes (Davahli, 2024). Leaders now function as facilitators who help teams use AI tools effectively and drive innovation while leading organizational transformation.

The implementation of AI in business strategies demands flexible digital-first thinking from project managers who need to adapt their strategies effectively.

Organizations experience multiple benefits from AI-based leadership systems yet they face critical challenges when transitioning to these systems. Leaders must receive ongoing training and leadership updates to develop their ability to learn and use AI tools effectively.

AI systems require human supervision to stop them from taking over jobs that belong to human professionals. As stressed by Davahli (2024), some areas in Project Management, such as crisis management or the encouragement of staff, still need intense human engagement and cannot entirely be trusted to AI.

1.3.3 Models for Measuring the Effectiveness of AI in Leadership

Project managers need to acquire new leadership methods and competencies because AI integration into project management systems changes all operational processes. Since most of the conventional leader work is being taken over by automation, there must be a different model of leadership in which analytical ability, information handling and human-computer coordination are competencies. The project manager used to handle project management and resource distribution and problem resolution but now requires new skills to achieve maximum AI benefits through learning predictive algorithms and data interpretation and AI-based decision support systems (Davahli, 2024).

Leaders now use AI-supported decision-making systems which transform their strategic planning and project execution methods. AI processes large datasets to create full performance evaluations of teams and project timelines and risk elements which project managers can use for immediate strategic choices (Dam et al.,2018). This does not mean that AI will take over leaders but that their role will more and more become strategic information management and essential interpretation of algorithmic data. Project management success will result from the combination of human instinct with AI-based analytical data.

A determining force is the change in the skill set required of project leaders. Traditional skills including communication and conflict management and team management will stay important yet they will receive support from new technology-based abilities. Joshi (2024) explains that AI chatbots have transformed stakeholder management through their impact on project leader-stakeholder communication. While previously communication required lots of human involvement, leaders must now be able to manage communication automation tools, monitor the performance of chatbots and intervene where greater relational sensitivity is required. The main goal involves teaching NLP competencies and AI-stakeholder communication skills to create technology-based solutions that enhance human relationships instead of deteriorating them. The implementation of AI in project management leads to organizational design changes and leadership role transformations which result in decentralized leadership models that replace traditional vertical leadership structures. The implementation of AI technology provides project teams with instant data access which enables them to function autonomously when making decisions (Davahli, 2024). Leaders now function as facilitators who help teams optimize AI tool usage and develop innovation cultures and organizational transformation initiatives. Project managers need to implement flexible digital-first methods for business strategy AI implementation to achieve successful AI integration. Organizations gain multiple benefits from

AI-based leadership systems yet they face critical barriers during their transition process. The main challenge organizations face during AI system adoption involves providing ongoing training programs for leaders to develop essential technical abilities needed for AI tool mastery. The system needs effective human oversight of AI operations together with human decision-making authority for critical choices. According to Davahli (2024) Project Management requires human involvement for crisis management and employee motivation because these areas need extensive human intervention beyond AI capabilities.

1.3.4 Examples of AI and Project Management in PBOs

The implementation of artificial intelligence technology transforms project-based organization leadership through its impact on resource management and decision processes and market adaptation capabilities. The two cases of Microsoft's Azure AI launch and IBM's AI implementation show how technology transforms entrepreneurial firm activity coordination and management.

1.3.4.1 Azure AI – Microsoft

The integration of Azure AI by Microsoft has brought about a major transformation in business leadership methods for project management and workflow optimization. Azure AI is a platform that enables companies to develop, implement, and scale machine learning models efficiently, offering a suite of advanced tools for data processing and decision-making automation. The introduction of this technology has allowed Microsoft to significantly improve the quality of strategic decisions, reducing the dependence on subjective intuitions of managers and instead increasing the reliability of data-driven forecasts (EconomyUp, 2024). A central aspect of this transformation is the integration with Dynamics 365, which has seen the development of autonomous agents capable of supporting managers in daily operations, improving resource management and optimizing the allocation of talent across project teams (Var Prime, 2024). With these tools, Microsoft PBO leaders have found it possible to focus more on strategic work and leave routine work and predictive analysis to AI. Microsoft has also invested in in-house training so that its workers can better understand the capabilities of artificial intelligence and use it within their work. It has encouraged the creation of a more responsive, dynamic work culture where leadership is supported by AI to respond better to market issues.

1.3.4.2 Watson AI – IBM

IBM has extensively implemented the use of artificial intelligence, particularly through Watson AI, an advanced system designed to process large volumes of data and provide strategic insights in real time. IBM has used Watson not only to improve its internal efficiency, but also to offer clients AI solutions applied to business management, healthcare, financial services and organizational governance. IBM has recently implemented new AI-based solutions for emissions monitoring and sustainable resource management, demonstrating how AI can be used to support more responsible and sustainability-oriented decisions (ESG News, 2024). In addition to operational efficiency, Watson has also transformed leadership in PBOs within the company. AI has been used to analyse resource allocation across projects, predict future workloads and reduce waste of time and human capital. Due to this technology, IBM executives are now able to make more informed decisions based on timely forecasts rather than history-focused analysis. Watson AI has brought cultural transformation to the organization through executive focus on developing data solutions for complicated issues and quick strategic decision-making.

1.4 Blockchain and Transparency: Governance Implications for AI-led Leadership

1.4.1 The Role of Blockchain in Corporate Governance

Blockchain is emerging as a game-changing technology for corporate governance, as it has the potential to offer transparency and decentralization of decision-making and operation control. Traditional corporate governance is based on centralised hierarchies and intermediaries, which control information management and operation control. The blockchain technology creates a new operational framework which depends on distributed consensus protocols and smart contracts to boost business process effectiveness and credibility (Khan et al. 2021).

Blockchain technology provides corporate governance systems with their fundamental value through its capability to create tamper-proof and transparent data storage systems. Blockchain technology functions as a decentralized system which generates permanent digital records for all transactions that function as unchangeable business operation traces (Hellani et al., 2021). The system delivers fundamental operational capabilities to organizations which require dependable internal and external audit performance because it protects data from tampering and establishes trust with stakeholders (Taherdoost, 2023).

Blockchain technology enables independent recording of business decisions and value exchanges between stakeholders through decentralized systems which reduce operational costs (De Filippi & McMullen, 2018).

Smart contracts function as digital agreements which execute automatically to automate corporate operations including supply chain management and shareholder dividend distribution (Naheed Khan et al.,2021). The automatic execution of smart contracts through predefined conditions leads to error-free operations while providing complete visibility of corporate policy execution (Taherdoost, 2023). Smart contracts demonstrate potential but their implementation faces three primary challenges because of security vulnerabilities and difficulties with contract modification and regulatory compliance (Naheed Khan et al.,2021).

Blockchain technology enables decentralized governance through consensus-based mechanisms which distribute decision-making power across network participants (De Filippi & McMullen, 2018). The decentralized autonomous organization (DAO) exemplifies this trend because it uses smart contracts to execute business and strategic decisions autonomously without centralized oversight (Khan et al. 2021). The proposed organizational structure enhances corporate governance performance through conflict reduction and organizational democratization (De Filippi & McMullen, 2018).

1.4.2 Smart Contracts and Leadership Automation

Smart contracts in corporate governance systems can automate leadership functions through new operational capabilities which blockchain technology enables for implementation in corporate governance systems. Self-executable and programmable digital instruments, they allow the implementation of business rules and decisions in an automated process with less human intervention and improved efficiency of decision-making processes (Khan et al.,2021). The combination of transparency and traceability and security features in smart contracts makes them an ideal solution for corporate leadership management to transform organizational management according to Taherdoost (2023).

Smart contracts present the most substantial opportunity to revolutionize how organizations handle their decision-making operations and corporate policy management. The programming of smart contracts allows for automatic execution of particular operations through pre-defined parameters which include budget distribution and project approval and employee incentive allocation (Naheed Khan et al.,2021). The system eliminates bureaucratic delays and protects against arbitrary or self-serving choices (De Filippi & McMullen, 2018). Smart contracts enable the automatic execution of company policies which results in both fair treatment and responsible behavior among employees.

Smart contracts play their most vital role in leadership automation through Decentralized Autonomous Organizations (DAOs) which function as blockchain organizations that use distributed consensus systems to make decisions based on coded rules (De Filippi & McMullen, 2018). The firms operate through smart contracts that establish corporate rules and resource distribution and member interaction management thus eliminating the requirement for traditional hierarchical structures (Khan et al.,2021). The system reduces management risks while providing transparent operations to support democratic business participation (Taherdoost, 2023).

1.4.3 Using Blockchain to Increase Transparency in AI-driven Decisions

The application of blockchain in AI-based decision-making systems is a strategic shift to increase business decision transparency, traceability, and reliability. Organizations currently implement AI technology at high speed to achieve operational efficiency and extract meaningful data insights for improved leadership decision making. AI models encounter a major challenge because their inability to generate understandable decision-making processes results in the "black box problem" as Taherdoost (2023) explains. The system loses its significance because blockchain technology allows for an unalterable record of AI algorithm operations which enables public inspection of decision-making procedures (Naheed Khan et al. 2021).

The essential section outlines the procedures for AI system decision registration and validation. A permissioned blockchain system enables AI systems to store complete decision-making records which include all applied metrics and used datasets and generated outputs.

This not only facilitates greater transparency but also traceability of algorithmic choices at a granular level, which can be audited and verified by regulators or internal stakeholders (De Filippi & McMullen, 2018). Moreover, blockchain integration renders the information upon which AI algorithms operate indestructible and untraceable through tampering, building trust in machine learning models on the basis of automated decision-making (Naheed Khan et al., 2021).

Another advantage of using blockchain for AI systems pertains to regulating algorithmic decision-making and decision accountability. In most organizations, AI algorithm decisions can have a significant impact on major business operations, including employee recruitment, lending, resource allocation, or portfolio selection. Blockchain technology enables smart contracts to link with AI models through which automatic decision implementation occurs when specific pre-defined and verifiable conditions are met (Taherdoost, 2023). The system decreases algorithmic bias risk through its ability to track and verify all decision-making steps (Naheed Khan et al. 2021).

Blockchain usage for data management in AI-driven decision-making is equally significant. AI algorithms show high sensitivity to the data quality and integrity which affects their training process and operational execution. However, accidental manipulation or alteration of data could be harmful to the quality of decisions arrived at by the algorithms. The implementation of blockchain technology for data validation and certification protects AI inputs from unauthorized tampering because it guarantees that all data remains authentic and unaltered (De Filippi & McMullen, 2018). The implementation of zero-knowledge proofs together with sophisticated encryption systems protects sensitive information from disclosure while maintaining the necessary transparency for monitoring according to Naheed Khan et al. (2021).

The application of blockchain in AI-based systems, nevertheless, also maintains some key challenges. The most crucial one concerns scalability since holding all the decisions and supporting information on the blockchain could be computationally expensive (Naheed Khan et al., 2021). Second, the need to find a balance between transparency and protecting intellectual property is of utmost priority to the majority of companies, especially those building proprietary AI models (Taherdoost, 2023). Finally, control of AI systems remains an emerging field, and integration with blockchain requires further delineation of best practices and standards at the global level (De Filippi & McMullen, 2018).

1.4.4 EY OpsChain and the Role of Blockchain in Corporate Management

Application of blockchain in business administration has found one of its most advanced forms in EY OpsChain, an application developed by Ernst & Young for the improvement of traceability, transparency and automation of business and government processes. The case study is a concrete illustration of how the application of blockchain can improve the efficiency of governance and financial management, reducing dependence on go-betweens and increasing control over information flows (Silva et al., 2024).

EY OpsChain operates on a permissioned blockchain system which enables businesses and public organizations to track transactions live while controlling digital assets and enhancing smart contract-based decision support. The tokenization of assets through EY OpsChain delivers maximum transparency and cash flow optimization for public spending and government investment management (Silva et al., 2024). The Polygon blockchain system for transaction recording has created an unalterable framework which Taherdoost (2023) states enables complete auditability to prevent financial fraud and corruption.

The real-time transaction tracking and authentication capability of EY OpsChain provides enhanced internal control and decreased administrative expenses.

The system uses electronic tokens to represent assets, costs and transactions, hence simplifying the financial management process and minimizing it to human judgment or mistake (Silva et al.,2024). Smart contracts in EY OpsChain enable automatic contract and payment execution based on predefined conditions which eliminate business process delays and inefficiencies (Naheed Khan et al.,2021). The blockchain technology implementation extends beyond conventional accounting management because it enables supply chain management and regulatory compliance and human resources management systems. The implementation of blockchain technology enables companies to verify tax and accounting compliance which helps prevent sanctions and streamlines auditing processes for control bodies (De Filippi & McMullen, 2018). EY OpsChain showcases blockchain technology supply chain management advantages through product tracking which authenticates origins and checks quality while preventing counterfeits (Silva et al. 2024).

The implementation of blockchain technology within business regulation brings about internal governance optimization as a key advantage. Decentralized models enable businesses to reduce their dependence on centralized decision-making through democratic systems that use voting mechanisms and distributed consensus methods (Taherdoost, 2023). The technology provides its most valuable benefits to complex organizations with multiple stakeholders because blockchain systems establish transparent governance systems for verification (De Filippi & McMullen, 2018).

1.5 AI and Leadership Challenges: Balancing Automation and Human Decision-Making

1.5.1 The Dilemma between Human Leadership and AI-driven decision-making

The implementation of AI decision-making in technological systems leads to changes in leadership positions but organizations must determine how human leaders will work with machines in organizational management. The major challenge is one of matching the analytical and predictive capabilities of AI with human emotional intelligence, creativity and moral judgment inherent in human leadership.

AI offers an unparalleled ability to process vast amounts of data in real time, finding complex patterns and guiding decisions with unbiased evidence (Wang, 2021). This offers the ability to reduce uncertainty and increase efficiency in decision-making processes, a particularly relevant advantage in cases where complexity and dynamicity are extreme. But being purely data-driven may be incompatible with the demands of decisions taken in accordance with moral values and ethical principles, elements that are inherently human (Alufaisan et al., 2021). For example, if a computer program suggested wholesale redundancies to reduce costs, a human manager would also take into account the social and emotional costs of making such a decision, preventing possible alienation of employees.

Another important area is the understanding and degree of reliance on AI-supported decisions. Although there has been some research to suggest that artificial intelligence can improve the quality of human decisions, there is no definite proof that explainable AI will necessarily improve the quality of decisions because humans tend to employ heuristics and cognitive biases that can limit their ability to accurately understand the information provided by AI systems (Alufaisan et al., 2021). Furthermore, trust in AI suggestions can be undermined by a perceived lack of transparency, leading leaders to over- or under-estimate algorithmic recommendations. Organizationally, the issue is further compounded when considering the change leadership role in facilitating AI adoption in companies. A study survey in the banking and service industry showed that AI has a positive impact on not just the performance of employees but also the engagement of employees if it is accompanied by effective leadership that can infuse technological change with appropriate human support (Wijayati et al., 2022). Without effective leadership, the application of AI can bring about hostility and frustration among workers, reducing its effectiveness.

1.5.2 Organizational resistance and barriers to AI adoption in leadership

Despite growing interest in the application of artificial intelligence (AI) in leadership, organizations are facing deep resistance and barriers to adoption. These issues arise from a combination of cultural, structural and psychological issues that influence leaders and employees, slowing the pace of digitalisation.

Resistances to change are among the most significant obstacles, as the managers and the employees fear AI could undermine their decision-making abilities or even make their roles obsolete (Wijayati et al., 2022). The perception that AI technology would be able to substitute human discretion can lead to insecurity and doubt, which creates reduced cooperation and AI-enabled technologies' acceptance. Particularly, the traditional leaders who previously made decisions on experience and intuition may think that AI is an instrument of undermining their power rather than being an enhancing tool (Alufaisan et al., 2021). This resistance is heightened due to the lack of certainty on how algorithms work that may lead to an inference of opacity and lack of reliability in machine-made decisions.

Another inherent impediment is the technical and organizational complexity of AI implementation. The application of advanced systems requires adequate infrastructure, significant financial investment and certain skills which most organizations do not possess. Lack of digital skills among management and operational staff poses a significant brake, as without adequate training, leaders might not be able to adequately analyse and utilize the information generated by AI (Wang, 2021). Besides, organizations with hierarchical systems and centralized decision-making are less likely to embrace AI tools because these require a change in the leadership model and data management strategy.

The implementation of AI hiring processes faces two major obstacles because of algorithmic prejudices and ethical concerns about AI system functionality. AI systems that learn from biased data either enhance discriminatory patterns or produce unproductive results which leads to decreased employee and leader trust in system reliability (Alufaisan et al.,2021). Organizations face two major obstacles to adopting these technologies because their algorithms operate with unclear decision-making processes and their internal workings remain impossible to understand (black box problem). The core element for resolving these obstacles exists in change leadership. Organizations that want to decrease AI resistance need leaders who support inclusivity and openly demonstrate AI advantages while actively involving staff members in transformation efforts (Wijayati et al.,2022).

Organizations need to develop a learning-oriented culture that unites human intelligence with AI systems to minimize resistance and achieve successful implementation.

1.5.3 How to balance automation and human decision-making?

Leadership development through artificial intelligence implementation demands careful management between machine-based decision automation and human involvement in decision processes. Organizations need human intelligence to lead their operations because AI systems lack the capability to replace human decision-making authority in leadership roles. The key challenge emerges from determining governance structures which will optimize AI advantages without diminishing human leadership value.

The first step to achieve AI-human decision equilibrium involves creating a hybrid system which uses AI for analytical support instead of decision-making replacement. AI systems excel at processing extensive data sets while detecting patterns and generating factual predictions (Wang, 2021). Strategic decision-making needs human interpretation because machines lack the ability to understand relationships and ethics when dealing with incomplete or uncertain data. AI systems that work with human leaders create a balanced partnership which allows them to combine AI's analytical strength with leaders' capacity to grasp ethical and relational aspects (Alufaisan et al.,2021).

One of the key features of this integration is algorithmic transparency, which allows leaders to view the rationale behind AI recommendations and improve decision-making when necessary. According to research, although AI may improve decision accuracy, unexplainability may reduce trust and uptake of algorithmic suggestions (Alufaisan et al., 2021). Explainable AI (XAI) systems are therefore required to be deployed in order to ensure that leaders are able to interpret AI outcomes and integrate them into decision-making without blindly relying on technology

Chapter 2 - Research methodology

2.1 – Research Method: Quantitative Approach and Hypothesis Development

2.1.1 – Methodological choices and research objectives

Organizations face a permanent shift in leadership operations because artificial intelligence has become the primary decision-making force in modern organizations. In particular, in project-based organizations, the impact of AI is even more significant since the flexibility and multidisciplinarity of projects further increase the input of intelligent technologies in the management of resources, time, and competencies. To this end, being aware of how AI is transforming the practice and expectations of leadership is not an academic concern, but a practical one in dealing with the realities of work organization in the 21st century. This research therefore endeavours to explore and understand, through empirical data, how and to what extent the advent of artificial intelligence actually influences the effectiveness and reputation of leaders in dynamic and complex organizational contexts.

2.1.2 – Quantitative approach and theoretical justification

In order to address this complexity in a structured manner, a quantitative research approach was adopted, which allows theoretical constructs to be translated into observable variables and their intensity, direction, and correlations to be measured within a defined sample. The quantitative method is particularly effective in cases where conceptual models are to be tested by verifying hypotheses, while offering the possibility of generalising the results within the limits imposed by the experimental design (Creswell, 2014). In addition, standardisation of instruments enables replicable and objective analysis, which is a prerequisite for the generation of sound and checkable empirical evidence (Bryman, 2012).

This method also permits the effective handling of data from large groups, enabling the detection and interpretation of relationships among variables. It is thus highly appropriate to the aim of this research, which is to stringently examine the relationships between the use of smart technologies and main dimensions of leadership in organizational settings

2.1.3 – Data collection tool and theoretical constructs

In line with these premises, this research aims to investigate, through the use of a structured questionnaire, the relationship between different factors: the adoption of AI, trust in automated processes, perceived transparency, the development of managerial skills and, finally, the effectiveness of leadership as experienced by project team members. The questionnaire, created using Google Forms, consists of closed-ended questions and seven-point Likert scales, capable of measuring the degree of agreement/disagreement with a series of theoretically grounded statements.

The research is theoretically informed by drawing inspiration from recent research examining the relationship between technology and leadership in digitalised environments (Shamim et al., 2020; Paudel et al., 2023). In particular, it is supposed that artificial intelligence does not merely support decisions but assists in redefining the very nature of the managerial role, reframing the emphasis from control to facilitation. This theoretical strand highlights AI's active and complementary role with respect to human competences, theorising that the potential of intelligent technologies lies not in their ability to replace managers, but to enhance their work and scale the impact of their strategic decisions.

2.1.4 – Research question and hypothesis

The research question guiding this work is:

“How is artificial intelligence redefining leadership in project-based organizations?”

Starting from this central question, a conceptual model has been developed that includes independent, dependent and mediating variables and aims to verify specific relationships through statistical analysis.

The research hypotheses formulated are as follows:

- H1: The adoption of artificial intelligence tools by leaders is positively associated with the perception of leadership effectiveness in project contexts.
- H2: The perceived transparency and ethicality of AI use by leaders positively influences the level of trust placed in the leader.
- H3: The integration of AI into managerial decision-making processes contributes to the development of new managerial skills required to operate in digitalised environments.
- H4: The extent of AI adoption in organizational processes is positively associated with the perception of leadership effectiveness and strategic consistency.

The hypotheses will be tested in the empirical analysis phase, using statistical techniques such as descriptive analysis, correlation and multiple regression. The expected results should help clarify the extent to which leadership can be enhanced — or hindered — by the adoption of artificial intelligence in project contexts, offering concrete insights for theoretical reflection and practical application in organizations.

2.2 – Questionnaire structure: variables, scales and validation

2.2.1 – General composition and conceptual structure of the questionnaire

The questionnaire was designed to collect data consistent with the conceptual model outlined in section 2.1, with the aim of empirically testing the relationships between the adoption of artificial intelligence in managerial contexts and the perception of leadership effectiveness in project environments. Administered through Google Forms, the questionnaire is structured in two sections: the first is dedicated to the collection of socio-demographic and professional data, while the second focuses on theoretical variables.

The initial section collects information on gender, age, educational qualifications, years of experience, role held, economic sector and size of the organization. These data allow us to characterise the sample and carry out exploratory analyses of any differences between subgroups. The second part of the questionnaire focuses on the nine variables identified in the theoretical model, divided into independent, mediating and dependent variables. Each variable is operationalised through a series of statements evaluated using a seven-point Likert scale.

2.2.2 – Independent variables

In the adopted conceptual model, the independent variables are the main explanatory factors, i.e. the elements that can directly or indirectly influence the perceived effectiveness of AI-supported leadership. These variables play a decisive role in determining the extent to which AI is adopted in managerial practices and related organizational perceptions. Their selection is based on established theoretical evidence and a careful selection of dimensions relevant to digitalised work contexts.

The six independent variables selected were identified from recent literature on the managerial implications of AI adoption. They allow us to analyse the technological and perceptual determinants that influence the performance of AI-augmented leadership.

- *Adoption of AI in Managerial Decision-Making (*Venkatesh & Bala;2008)*: assesses the extent to which managers incorporate AI tools into daily decision-making activities*
- *Trust in AI-Based Decision-Making (*Schneider, Süß & Wehner;2022)*: measures the extent to which team members have confidence in the output generated by AI-supported decision-making models.AI-Enabled*
- *Managerial Competencies (*Davis;1989): assesses the managerial competencies perceived as necessary for the effective use of AI in leadership.
- *Perceived Transparency of AI Systems (*Schnackenberg & Tomlinson;2016): investigates the degree of clarity and comprehensibility attributed to automated decision-making processes.
- *Perceived Reliability of AI Outputs (*Schnackenberg & Tomlinson;2016): examines the perception of consistency, accuracy and technical dependence of the results generated by intelligent systems.
- *Ethical and Privacy Perception of AI (*Malhotra, Kim & Agarwal;2004): measures the level of ethical compliance and privacy perceived in adopted AI systems.

2.2.3 – Mediating and dependent variables

Mediating variables are a crucial element in analysing the process through which independent variables produce their effect on the dependent variable. They play a cognitive and perceptual mediation function, elucidating the psychological and organizational processes linking AI adoption and leadership effectiveness. They allow us to construct a more realistic and stratified model, capable of explaining complex phenomena through indirect effects. At the same time, the dependent variable is the final outcome of the process under analysis, i.e. the level of effectiveness attributed to leaders who adopt AI tools within project environments

Two mediating variables are hypothesised within the model:

- *Trust in AI-Driven Leadership (*Schneider, Süß & Wehner;2022): reflects the trust that employees place in leaders who adopt artificial intelligence tools.
- *Perceived Usefulness of AI in Leadership (*Davis;1989): measures the perceived usefulness of artificial intelligence in increasing the efficiency, accuracy and adaptability of leadership.

The dependent variable is:

- *AI-Driven Leadership Effectiveness (*Kouzes & Posner;1988): measures the degree of perceived effectiveness of the leader in using AI to achieve goals, manage resources and positively influence the team.

Together, these variables form the basis of the conceptual model tested in this study.

2.2.4 – Measurement scales and validation of the tool

All variables were measured using items rated on a 7-point Likert scale, where 1 corresponds to 'Completely disagree' and 7 to 'Completely agree'. This choice, in line with Finstad's methodological recommendation (2010), allows for high sensitivity in the detection of subjective perceptions.

The items were derived from scales already validated in previous studies (Shamim et al., 2020; Paudel et al., 2023) and appropriately adapted to the context of Project-Based Organizations. Content validity was obtained through researcher and expert review. In addition, a pilot study on ten respondents was conducted to test for clarity and internal consistency, as well as to estimate the average completion time, which was determined at approximately seven minutes. The Table 1 below summarises the measurement scales used:

Construct	*No. of items*	*Scales*	*Source*
Gender	1	1 = Male, 2 = Female, 3 = Prefer not to answer	
Age group	1	1 = Under 25, 2 = 25–34, 3 = 35–44, 4 = 45–54, 5 = 55+	
Role in the organization	1	1 = Manager, 2 = Team Leader, 3 = Specialist, 4 = Technical role, 5 = Other	
Years of experience	1	1 = less than 2 years, 2 = 2–5 years, 3 = 6–10 years, 4 = more than 10 years	
Organizational context	1	Open text	
Organization size	1	1 = <10, 2 = 11–50, 3 = 51–250, 4 = 251–500, 5 = >500 employees	
AI-driven leadership effectiveness	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Kouzes & Posner (1988)
Trust in AI-Driven Leadership	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Schneider, Süß & Wehner (2022)
Perceived Usefulness of AI in Leadership	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Davis (1989)
Adoption of AI in Managerial	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Venkatesh & Bala (2008)

Decision-Making			
Trust in AI-Based Decision-Making	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Schneider, Süß & Wehner (2022)
AI-enabled managerial competencies	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Davis (1989)
Perceived Transparency of AI Systems	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Schnackenberg & Tomlinson (2016)
Perceived Reliability of AI Outputs	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Schnackenberg & Tomlinson (2016)
Ethical and Privacy Perception of AI	5	7-point Likert scale: 1 = Completely disagree, 7 = Completely agree	Malhotra, Kim & Agarwal (2004)

Table 1: Measurement scales and research variables

2.3 – Sampling strategy, data collection and statistical processing

The methodological strategy adopted for data collection is consistent with the epistemological framework of the research and with the exploratory and analytical nature of the survey. The research employed purposive sampling because this technique serves as a standard approach in organizational studies to acquire data from participants who match the research subject criteria (Etikan et al. 2016). The method enabled researchers to identify professionals and managers and collaborators who work in project environments and provide expert and conscious insights about artificial intelligence applications in leadership. The data collection process used an online questionnaire built on Google Forms which enabled easy distribution to many users and straightforward management of their responses. Anonymity was guaranteed and data was processed in compliance with current privacy regulations, in particular EU Regulation 2016/679 (GDPR). The research included 100 participants who met the required number for statistical power according to Hair et al. (2014) for studies based on regression and mediation models. The inclusion criteria were: age over 18, at least one current or previou l work experience, fluent knowledge of English and familiarity with digital tools and smart technologies. These criteria allow the sample to be limited to individuals potentially exposed to organizational practices geared towards technological innovation. The data collected will be exported in Excel format and then processed using SPSS (Statistical Package for the Social Sciences) software, widely used in social research for its versatility in developing advanced statistical models. The statistical processing will be structured in several sequential and complementary phases: Descriptive analysis of socio-demographic variables and theoretical constructs, aimed at identifying central trends and dispersion (means, standard deviations, frequencies); Verification of the internal reliability of the measurement scales by calculating Cronbach's alpha, with an acceptability threshold of ≥ 0.70 (Nunnally & Bernstein, 1994); Bivariate analysis of correlations between the main variables using Pearson's coefficient; hypothesis testing of mediation using Hayes' PROCESS Macro, which allows indirect and moderate effects to be estimated in simple and multiple mediation models (Hayes, 2017); Any analyses of differences between groups using t-tests for independent samples or ANOVA, depending on the nature of the categorical variables identified in the socio-demographic section. This comprehensive sampling and data processing strategy meets the need to ensure methodological rigour, internal validity and contextual generalisability, in line with the standards of empirical research in applied social sciences.

Chapter 3 – Data analysis and results

This chapter aims to present and discuss the results emerging from the empirical analysis conducted on the dataset collected through the questionnaire. The survey was designed to investigate the relationships between the adoption and perception of artificial intelligence in managerial contexts and the transformation of leadership models, with a specific focus on Project-Based Organizations (PBOs).

To guide the reader, Figure 1 illustrates the research model tested in this study. The model hypothesises that AI adoption and perception, articulated into distinct dimensions, influence leadership effectiveness both directly and indirectly. Specifically, managerial integration of AI (adoption, trust in AI-based decision-making, and AI-enabled competences) and perceived system qualities (ethics, transparency, and reliability) are posited as independent variables. These, in turn, act through two mediating mechanisms: trust in AI-driven leadership and the perceived usefulness of AI in leadership. Together, these factors converge on the dependent variable: AI-driven leadership effectiveness.

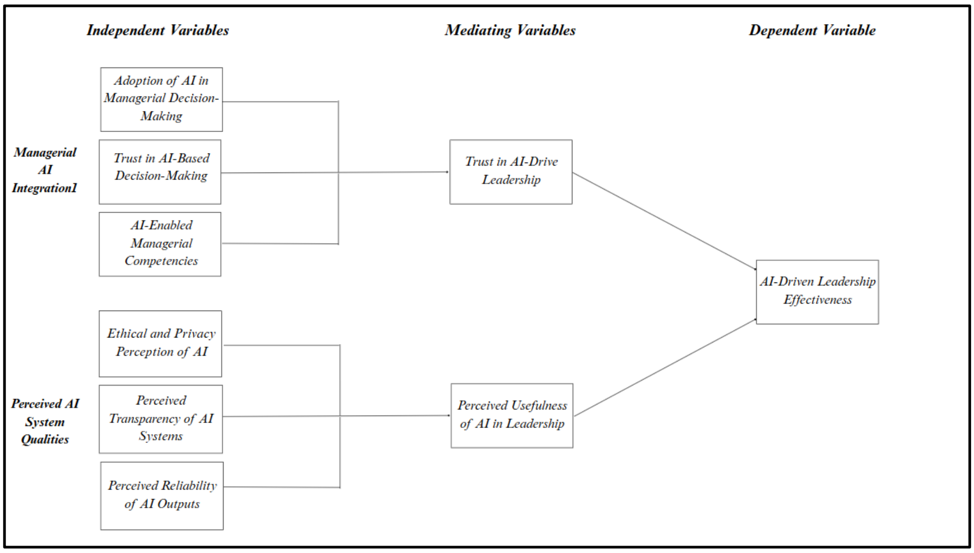

Figure 1: Research Model

The model in Figure 1 combines two aspects to study AI effects on project-based leadership by analyzing cognitive elements (usefulness, transparency, reliability) and relational aspects (trust, ethics). The research investigates direct effects through psychological and organizational mechanisms to understand how AI adoption affects leader effectiveness perceptions.

Methodological note

The statistical analyses were performed using Python programming language through the combination of Pandas for data handling and NumPy for numerical computation and Statsmodels for regression and inferential analysis and Pingouin for mediation and Matplotlib for result visualization. The Python programming language provided both rigorous and adaptable functionality during the process stages which allowed full control of data and models. The following sections use empirical evidence to validate the hypotheses established in Chapter 2. The evaluation process for these results takes place in Chapter 4 which analyzes results and their theoretical and managerial implications.

3.1 Descriptive statistics

3.1.1 Socio-demographic profile of the sample

The reference sample consists of 104 respondents from a variety of organizational and professional contexts. The age, occupational and organizational distribution makes it possible to outline a varied profile consistent with the objective of investigating the relationship between artificial intelligence and leadership in project-based contexts.

Regarding the gender variable, a slight predominance of women emerges, with 54.8% of the respondents identified as women and 43.3% as men, while 1.9% preferred not to specify gender. The distribution maintains equal numbers of male and female participants which stops any potential bias that could emerge from group dominance.

The 25-34 age group represents the biggest demographic since it makes up 43.3% of total survey participants. The working force consists mainly of people aged 35-44 years (24%) and Under 25 years (15.4%) according to the data. The working force consists mainly of younger employees since the 45-54 years and 55+ years age groups represent only a small but important portion of the workforce. The educational qualification data indicates that participants possess advanced educational backgrounds since three-year degree holders make up 47.1% of the group and master's degree holders amount to 29.8%. 17.3% have a high school diploma, while those with a doctorate or equivalent are 2.9%, the same percentage as those who indicated 'other'. This cultural profile indicates a high propensity to adopt and understand emerging technologies, such as artificial intelligence.

As far as the professional role held is concerned, a good distribution among different organizational functions can be observed. Team leaders represent 30.8% of the sample, followed by managers (26%), technical staff (14.4%) and administrative staff (15.4%). A further 13.5% indicated 'other', demonstrating the transversal nature of the roles involved in the survey.

The seniority in the role reflects a clear prevalence of professionals at an early or intermediate stage of their career: 48.1% of the participants have between 1 and 3 years of experience, while a further 25% declare a seniority between 4 and 6 years. Professionals with more than 10 years of experience account for 8.7%, as do those with between 7 and 10 years in the role. The youngest group in terms of experience (<1 year) constitutes 9.6% of the total.

As for the size of the organizations they belong to, there is a good variety: 35.6% of the participants work in companies with 50-249 employees, while smaller organizations (<50 employees) and larger ones (>1000 employees) are equally distributed with 25% and 19.2% respectively. Medium-sized enterprises (250-999 employees) cover the remaining 20.2%, confirming a good coverage of all size segments.

The sample also shows an interesting sectoral breakdown. 26.9% operate in the technology sector, followed by education and health services (both at 14.4%), finance (8.7%), manufacturing (8.7%), public administration (6.7%), and 20.2% falling into the 'other' category. The significant representation of the technology sector is consistent with the focus of the survey. Finally, the rate of artificial intelligence adoption in organizations is high: 91 of the respondents (88%) indicate that their organization uses artificial intelligence tools; just 10 of the respondents (9.6%) affirm that AI is not currently used in their setting, and the remaining 2.9% are not sure. This figure testifies to an expanding diffusion of smart technologies in contemporary organizations, which confirms the relevance and topicality of the survey.

Constructs	*Categories*	*N*	*%*
Gender	Male	45	43,3%
	Female	57	54,8%
	Prefer not to say	2	1,9%
Age	Under 25	16	15,4%
	25-34	45	43,3%
	35-44	25	24,0%
	45-54	11	10,6%
	55+	7	6,7%
Educational Qualification	High school diploma	18	17,3%
	Bachelor's degree	49	47,1%
	Master's degree	31	29,8%
	PhD or equivalent	3	2,9%
	Other	3	2,9%
Job Role	Manager	27	26,0%
	Team leader	32	30,8%
	Technical staff	15	14,4%
	Administrative staff	16	15,4%
	Other	14	13,5%
Seniority in the current role	< 1 year	10	9,6%
	1-3 years	50	48,1%
	4-6 years	26	25,0%
	7-10 years	9	8,7%
	> 10 years	9	8,7%
Size of the organization you work for	< 50 employees	26	25,0%
	50-249 employees	37	35,6%
	250-999 employees	21	20,2%
	> 1000 employees	20	19,2%
Industry your organization belongs to	Technology	28	26,9%
	Manufacturing	9	8,7%
	Healthcare	15	14,4%
	Finance	9	8,7%
	Education	15	14,4%

	Public Administration	7	6,7%
	Other	21	20,2%
Use of AI in the organization	Yes	91	88%
	No	10	9,6%
	Not sure	3	2,9%

Table 2: Socio-demographic variables

3.1.2 Internal reliability of measurement scales

In order to ensure the consistency and quality of the measurements used in this research, Cronbach's Alpha internal reliability coefficient was calculated for each of the multi-item scales used. This index, widely recognised in psychometrics, allows the degree of internal correlation between the items of a scale to be estimated, indicating how consistently they contribute to the measurement of a single theoretical construct.
As can be seen from Table 3, all the variables analysed have alpha values well above the commonly accepted threshold of 0.70, and in many cases are close to or above 0.95, confirming excellent internal reliability.

Variable	Cronbach's Alpha	95% CI Lower	95% CI Upper
AI LDR	0.959	0.944	0.971
Trust LDR	0.946	0.926	0.962
Usefulness AI	0.958	0.942	0.970
Adopt AI	0.955	0.939	0.968
Trust AI	0.931	0.906	0.951
Comptence AI	0.950	0.931	0.964
Transparency AI	0.941	0.919	0.958
Realiability AI	0.939	0.917	0.957
Ethics AI	0.930	0.904	0.950

Table 3: Cronbach's Alpha

The AI_LDR measure, or the perception of the efficacy of AI-supported leadership, captures an α value of 0.959, which reflects a highly internal-consistent set of items on the scale. Equally, extremely high values are also observed for Usefulness_AI (α = 0.958) and Adopt_AI (α =

0.955) that capture the construct validity of the scales used to measure, respectively, perceived usefulness of AI in leadership and the level of AI adoption in managerial decision-making.
All the other variables likewise exhibit outstanding levels of reliability, with α values greater than 0.93 in all instances for the main constructs of trust (Trust_AI, Trust_LDR) and perceived system quality (Transparency, Reliability, Ethics). The confidence intervals are likewise close and uniform, further evidence of the accuracy of the estimates.
In general, the resultant findings confirm the scales of measurement applied and provide an effective methodological basis for future statistical analysis.

3.1.3 Descriptive statistics of research variables

The variables surveyed were measured on a 7-point Likert scale and summarised by averaging the five items provided for each construct. In order to provide an initial interpretative orientation, this section analyses the main descriptive statistics of each theoretical dimension surveyed, with particular attention to distribution, internal variability and centrality of scores.
The dependent variable of the model, AI-Driven Leadership Effectiveness (AI_LDR), has a mean value of 4.78, whose standard deviation is 1.70. Its corresponding value of 5.00 is the median, and its maximum is 7.00, whereas its minimum is 1.00. Its first quartile, Q1, is 3.63, and its third quartile, Q3, is 6.25. Its distribution appears to be wide and relatively symmetrical, albeit inclined towards medium-high values. Although responses are present across the scale, the prevailing concentration above the threshold value of 4 signals a generally positive perception of the effectiveness of AI-enabled leadership.
The construct Trust in AI-Driven Leadership (Trust_LDR), shows a mean of 5.20 and a standard deviation of 1.47, with a median value of 5.60 as well. The quartiles show an intermediate distribution: Q1 = 4.55, Q3 = 6.20. Once more, the range spans the whole interval (min = 1, max = 7), but the data seem to be grouped in the mid-high range. This verifies a general faith in AI-assisted leadership, even if with certain inter-individual variations.
The variable Perceived Usefulness of AI in Leadership (Usefulness_AI) has a mean value of 5.13, standard deviation 1.60. The median value is 5.60, and all values from 1.00 to 7.00 are within its range. The first quartile is 4.15, and the third is 6.40. This is therefore a substantially positive distribution, with a large proportion of respondents recognising the usefulness of artificial intelligence in decision-making and team leadership. But the non-negligible standard deviation also reveals the existence of more cautionary or critical responses.

The dimension Adoption of AI in Managerial Decision-Making (Adopt_AI), which is an index of current usage of artificial intelligence in managerial decision-making, has a mean of 4.44, and its standard deviation is 1.72. Its median is 4.80, and its quartiles lie between 3.20 (Q1) and 5.80 (Q3). In comparison with all the other constructs, this variable lies closer to the value of neutrality on the scale, which implies a situation that is yet unfolding: many managers started taking advantage of AI tools, but adoption isn't widespread nor homogeneous in all scenarios. The minimum value of 1 and the highest standard deviation across all variables support the notion that this phenomenon remains unbalanced and partially based on personal experience.

The Trust in AI-Based Decision-Making (Trust_AI) scores an average of 5.12 with a standard deviation of 1.51. The middle value of Trust in AI-Based Decision-Making (Trust_AI) reaches 5.60 while the first quartile (Q1) equals 4.40 and the third quartile (Q3) equals 6.20.

The majority of respondents rate AI program outputs as highly trustworthy according to the right-skewed distribution of ratings.

The construct AI-Enabled Managerial Competencies (Competence_AI) measures unique managerial abilities for artificial intelligence management with a mean score of 5.15 and standard deviation of 1.49. The data distribution shows a median of 5.40 while the first quartile (Q1) reaches 4.35 and the third quartile (Q3) reaches 6.40. The overall assessment indicates managers possess suitable awareness about new technologies yet they require additional specialized training to handle these systems effectively.

The mean value of Perceived Transparency of AI Systems (Transparency_) stands at 5.14 while its standard deviation is 1.41 and the median equals 5.50 and the range extends from 1 to 7. Quartiles range from 4.20 to 6.40, which indicates that although automated decision-making processes' transparency is positively viewed through the lens of the majority of respondents, there is also a level of doubt for a proportion of the sample that still is sceptical.

The variable Perceived Reliability of AI Outputs (Reliability_) also ratifies this pattern of interpretation, with mean 4.91 and standard deviation 1.40. The median is 5.00, quartiles ranging from 4.35 to 6.00. The graph reveals that perception about the technical reliability of AI systems is on average positive, yet lower than in other dimensions, likely due to the impact of occasional failures, absence of human control or doubts regarding algorithms that lie beneath.

Lastly, the construct Ethical and Privacy Perception of AI (Ethics_) has a mean value equal to 4.86 and standard deviation equal to 1.51. The median value is equal to 5.00, and its distribution range is 1.00-7.00, with quartiles ranging between 4.00 and 6.05. This is likely to be the dimension with highest interpretative heterogeneity: although, on the one hand, respect for ethics and for privacy is perceived as being satisfactory, on the other, some interviewees still profess a certain level of confusion and mistrust, which evidences the interest in reinforcing assurances and transparency regarding algorithmic governance. In general, descriptive statistics reiterate that artificial intelligence tends to be viewed favorably across those who implement it or experience it within organizational and managerial settings. The responses from the participants present a positive portrait yet one that is not without complexity, with points (adoption, ethics, reliability) that warrant special attention with respect to development, training and regulation. Analysis of correlations and subsequent regressions will therefore be crucial in clarifying how these perceptions concretely influence leadership effectiveness in digitised environments.

Constructs	*Categories*	*N*	*%*
AI-Driven Leadership Effectiveness	1	4	4%
	2	9	9%
	3	13	13%
	4	12	12%
	5	20	19%
	6	25	24%
	7	21	20%
Trust in AI-Driven Leadership	1	1	1%
	2	7	7%
	3	9	9%
	4	9	9%
	5	23	22%
	6	35	34%
	7	20	19%
Perceived Usefulness of AI in Leadership	1	3	3%
	2	6	6%
	3	9	9%
	4	14	13%
	5	19	18%
	6	28	27%
	7	25	24%
Adoption of AI in Managerial Decision-Making	1	7	7%
	2	12	12%
	3	10	10%
	4	16	15%
	5	26	25%
	6	25	24%
	7	8	8%
Trust in AI-Based Decision-Making	1	3	3%
	2	6	6%
	3	6	6%
	4	18	17%
	5	18	17%

	6	36	35%
	7	17	16%
AI-Enabled Managerial Competencies	1	2	2%
	2	6	6%
	3	6	6%
	4	18	17%
	5	24	23%
	6	24	23%
	7	24	23%
Perceived Transparency of AI Systems	1	2	2%
	2	3	3%
	3	9	9%
	4	17	16%
	5	21	20%
	6	34	33%
	7	18	17%
Perceived Reliability of AI Outputs	1	2	2%
	2	9	9%
	3	5	5%
	4	14	13%
	5	37	36%
	6	24	23%
	7	13	13%
Ethical and Privacy Perception of AI	1	2	2%
	2	8	8%
	3	8	8%
	4	21	20%
	5	26	25%
	6	21	20%
	7	18	17%

Table 4: Descriptive statistics of research constructs

3.2 Correlation analysis: relationships between AI adoption and leadership variables

In order to preliminarily explore the linear relationships between the variables under study, a bivariate correlation analysis was conducted according to Pearson's coefficient. This procedure made it possible to identify any statistically significant associations between the theoretical dimensions detected, providing a useful empirical basis both for the interpretation of the data and for the structuring of subsequent regression and mediation analyses.

The analysis produced a dense matrix of robust relationships after the constructs underwent averaging based on the previous section's description. The analysis produced high correlations ranging from 0.60 to 0.90 with p values below .001 except for two instances. The results show strong conceptual unity between the constructs because the theoretical framework supports this outcome.

The questionnaire's main construct AI-Driven Leadership Effectiveness (AI_LDR) shows strong relationships with multiple essential explanatory variables. The relationship between AI-Driven Leadership Effectiveness (AI_LDR) and Adoption of AI in Managerial Decision-Making (Adopt_AI) reaches an extremely high level of 0.86. The strong correlation indicates that managers who use AI in their decision-making processes receive higher effectiveness ratings as leaders. The scale value approaches its theoretical maximum which demonstrates a direct link between technology adoption and leadership performance.

The study shows that AI_LDR has a strong relationship with Trust in AI-Driven Leadership (Trust_LDR) through their correlation coefficient of $r = 0.80$. The finding supports leadership theories which show trust functions as a key factor for effective leadership in smart technology adoption environments. The study shows that leaders who use AI for their work achieve better results when they believe AI tools help them perform their tasks ($r = 0.70$). The effectiveness of AI-based leadership depends on how useful leaders perceive AI to be for their managerial activities.

The relationship between Trust in AI-Based Decision-Making (Trust_AI) and AI_LDR stands at $r = 0.67$ but shows a lower connection than the other variables. The system trust factor shows lower influence on leadership effectiveness than both leader interpersonal trust and tool instrumental value.

The relationship between Competence_AI (AI-Enabled Managerial Competencies) and AI_LDR reaches $r = 0.69$ which demonstrates that proper managerial competencies for AI tool management directly impact leadership success. The study confirms digital leadership research

which emphasizes digital hard and soft skills as essential competencies for digital transformation success.
The variables Transparency_ and Reliability_ demonstrate strong correlations with AI_LDR at r = 0.73 and r = 0.72 respectively. The high correlation values indicate that AI explainability and operational consistency play essential roles in creating leadership perceptions of solidity and legitimacy.
The Ethical and Privacy Perception of AI (Ethics_) shows a positive relationship with AI_LDR (r = 0.62) which is the smallest but still significant correlation The figure indicates that people recognize ethics as important yet they have not fully absorbed its significance because they view ethics as important but not directly linked to leader performance although it could impact long-term trust development.
The correlation matrix demonstrates a unified theoretical structure because all constructs show strong connections with each other which supports the idea that AI-enabled leadership effectiveness emerges from balanced technological and cognitive and relational elements. The strong correlations between variables enable researchers to conduct further analysis of causal and mediated effects through multiple regression and mediation tests in the following sections.

3.3 Regression analysis: predicting leadership transformation through AI

3.3.1 Linear regression: Adoption of AI in Managerial Decision-Making

The first multiple linear regression model aims at investigating the influence of the adoption of artificial intelligence in managerial decision-making (Adopt_AI) on the perceived effectiveness of AI-supported leadership (AI_LDR). In line with the theoretical framework of the present work, the two main control variables provided by the conceptual framework are included in the model, namely trust in the leader (Trust_LDR) and perceived usefulness of artificial intelligence (Usefulness_AI).
The results of the model show a statistically significant and positive link between the variable Adopt_AI and the dependent variable AI_LDR. As indicated in Table 5, the estimated value for Adopt_AI is 0.576 (standard error = 0.097) with a very high level of significance ($p < 0.01$). The results show that when leaders maintain equal levels of trust and usefulness AI adoption in decision-making leads to better perceived leadership effectiveness.
The research shows that technology advancement alone does not lead to positive results because its actual implementation within managerial decision-making processes produces better leadership perceptions.

	(1)
Intercept	0.097
	(0.354)
Adopt_AI	0.576***
	(0.097)
Trust_LDR	0.381***
	(0.114)
Usefulness_AI	0.028
	(0.067)
R-squared	0.788
R-squared Adj.	0.782
N	104

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Linear Regression – Adoption of AI

The variable Trust_LDR demonstrates a positive relationship with 0.380 (SE = 0.114) at $p < 0.01$ which verifies that leader trust functions as an essential factor for AI-supported leadership model adoption. The Usefulness_AI variable shows a non-significant coefficient of 0.028 (SE = 0.067) which indicates that AI usefulness does not directly affect leadership effectiveness in this particular model. The three independent variables in the model explain 78.8% of the variation in perceived leadership effectiveness according to $R^2 = 0.788$.

This is very high explanatory power, consistent with the strength of the observed relationships. In sum, the first model provides solid empirical evidence in support of the central role of the concrete adoption of AI by managers as a predictor of leadership effectiveness. The result supports the theoretical hypothesis that the digital transformation of managerial practices emerges as a decisive lever for the legitimisation of managerial power in the AI era, provided that it is accompanied by adequate levels of trust and acceptance by employees

3.3.2 Linear regression: Trust in AI-Based Decision-Making

The second linear regression assessed the effect of the independent variable Trust in AI-Based Decision-Making on the perception of AI-Driven Leadership Effectiveness, controlling for the two mediators Trust in AI-Driven Leadership and Perceived Usefulness of AI in Leadership.As shown in Table 6, the results obtained show that the direct influence of trust in AI-supported decision-making processes is statistically non-significant, with a coefficient of -0.030 (standard error = 0.153). This result suggests that, all other factors being equal, the trust placed in AI systems does not make a significant direct contribution to the perception of leadership effectiveness.

	(1)
Intercept	-0.396
	(0.463)
Trust_AI	-0.030
	(0.153)
Trust_LDR	0.721***
	(0.140)
Usefulness_AI	0.307**
	(0.138)
R-squared	0.689
R-squared Adj.	0.680
N	104

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Linear Regression – Trust in AI

In contrast, the construct Trust in AI-Driven Leadership is once again confirmed as one of the most influential variables in the model, with a positive and highly significant coefficient of 0.721 (standard error = 0.140, $p < 0.01$). This finding reinforces the hypothesis that the trust placed in AI-mediated leadership is a decisive factor in the construction of a positive perception of managerial effectiveness.

The variable Usefulness of AI in Leadership also remained significant in the model, with a coefficient of 0.307 (standard error = 0.138, $p < 0.05$), indicating that the perceived usefulness of AI in leadership practices continues to exert a positive influence on the dependent construct. The model as a whole shows good explanatory power, with an R^2 of 0.689 and an adjusted R^2 of 0.680, values that signal that almost 69% of the variance in the perceived effectiveness of AI-driven leadership is jointly explained by the included variables. These results underline how, even in the absence of direct significance of the construct Trust in AI-Based Decision-Making, trust in leadership and perceived usefulness of AI are key drivers in understanding the phenomenon analysed.

3.3.3 Linear regression: AI-Enabled Managerial Competencies

The third linear regression model was developed to assess the influence of AI-enabled managerial competencies (Competence_AI) on perceived leadership effectiveness (AI_LDR).

Again, the control variables included in the model are Trust_LDR and Usefulness_AI, in line with the theoretical approach adopted throughout the chapter.

As shown in Table 7, the results obtained paint a complex picture. The coefficient associated with Competence_AI is 0.192, with a standard error of 0.146; this value is not statistically significant, suggesting that, given the same trust in the leader and perceived usefulness of AI, the perception of managerial skills alone in the use of artificial intelligence does not determine a significant direct impact on leadership effectiveness. This finding, although unexpected with respect to the initial hypotheses, can be interpreted as a function of the fact that technical skills alone are not enough: for them to generate tangible effects, they must be recognised, legitimised and embedded in a relational framework of trust.

	(1)
Intercept	-0.562
	(0.431)
Competence_AI	0.192
	(0.146)
Trust_LDR	0.695***
	(0.142)
Usefulness_AI	0.144
	(0.135)
R-squared	0.694
R-squared Adj.	0.685
N	104

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Linear Regression – AI-Enabled Managerial Competencies

On the contrary, the construct Trust_LDR is also confirmed in this model as the most relevant variable from a predictive point of view, with a coefficient of 0.695, significant at the 1% level (standard error = 0.142). Trust in the leader using artificial intelligence technologies once again emerges as an indispensable element in determining the quality of perceived leadership.

The variable Usefulness_AI, although showing a positive coefficient (0.144), does not reach the threshold of statistical significance (standard error = 0.135), showing a similar dynamic to that already observed in the previous models: the perceived usefulness of AI tends to strengthen leadership only in combination with other cognitive or relational factors.

The overall quality of the model nevertheless remains satisfactory, with an R^2 of 0.694 and a corrected R^2 of 0.685, values that confirm a good explanatory capacity, compatible with that observed in the other models. The explanation of almost 70% of the variance of the dependent construct reinforces the hypothesis of a solid and coherent theoretical structure, where, however, the role of technical managerial skills does not manifest itself with a direct effect but rather, presumably, through indirect or moderate mechanisms.

3.3.4 Linear regression: Perceived Transparency of AI Systems

The fourth regression model analysed the role played by the perceived transparency of artificial intelligence systems (Transparency) on the effectiveness of AI-supported leadership (AI_LDR). Consistent with the analytical structure of the chapter, the two central theoretical controls were retained in the model: Trust_LDR and Usefulness_AI.

As shown in Table 8, the results reveal a statistically significant relationship between the variable Transparency and perceived leadership, with a positive coefficient of 0.286 (standard error = 0.143) and significance at the 5% level. This finding suggests that, given equal trust in the leader and perceived usefulness of artificial intelligence, greater clarity in the decision-making processes of intelligent tools is associated with higher perceived leadership effectiveness. In other words, the transparency of the algorithm and the comprehensibility of its logic of action is a relevant element in enhancing the legitimacy and authority of leaders who use it.

	(1)
Intercept	-0.754*
	(0.433)
Transparency_	0.286**
	(0.143)
Trust_LDR	0.635***
	(0.154)
Usefulness_AI	0.147
	(0.123)
R-squared	0.710
R-squared Adj.	0.701
N	104

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Linear Regression – Perceived Transparency of AI Systems

As observed in previous models, Trust_LDR confirms its predictive power, with a coefficient of 0.635 (SE = 0.154), which is highly significant ($p < 0.01$). Trust in the leader remains a central dimension in promoting an effective and credible leadership image in digitised contexts.

The Usefulness_AI variable, though having a positive coefficient (0.147), fails to cross the margin of statistical significance, as was the case for previous models. This outcome lends support to the hypothesis that perceived AI usefulness can function indirectly, mediating or moderating other relationships rather than directly affecting the dependent construct.

Overall, the model explains a good level of variance of the AI_LDR construct, with an R^2 of 0.710 and a corrected R^2 of 0.701, values that confirm the effectiveness of the theoretical specification and the statistical goodness of the estimation performed.

Briefly, this analysis suggests that transparency of intelligent systems is a key concern when creating leadership for AI-based situations, calling attention to the importance of obtaining intelligible, open and accountable procedures. Transparency is not so much a technical characteristic as a strategic organizational value that assists in supporting the legitimacy and accountancy perceptions of the leader.

3.3.5 Linear regression: Perceived Reliability of AI Outputs

The fifth linear regression model focuses on analysing the effect of the perceived technical reliability of the results produced by artificial intelligence (Reliability) on the dependent variable AI_LDR, which represents the perceived effectiveness of AI-enabled leadership. Again, the model includes the two theoretically central control variables Trust_LDR and Usefulness_AI.

The results, shown in Table 9, show that the Reliability variable is not a statistically significant predictor of leadership effectiveness. The estimated coefficient is -0.032 (standard error = 0.121), and the relative p-value does not allow the null hypothesis to be rejected. This suggests that, given equal trust in the leader and perception of the usefulness of AI, the technical reliability of the results provided by intelligent systems alone is not sufficient to generate an improved perception of leadership. This is an interesting finding, which seems to indicate that the strictly engineering aspect of AI output, although operationally relevant, is not necessarily a direct perceptual driver of effective leadership.

	(1)
Intercept	-0.378
	(0.465)
Reliability_	-0.032
	(0.121)
Trust_LDR	0.708***
	(0.139)
Usefulness_AI	0.318**
	(0.139)
R-squared	0.689
R-squared Adj.	0.680
N	104

Standard errors in parentheses.
$* p < 0.1,\ ** p < 0.05,\ *** p < 0.01$

Table 9: Linear Regression – Perceived Reliability of AI Outputs

In contrast, trust in the AI-supported leader (Trust_LDR) is again confirmed as the main positive predictor of the AI_LDR construct, with an estimated coefficient of 0.708 (standard error = 0.139), highly significant at the 1% level. This finding reinforces the trend observed in previous models, highlighting a structural and consistent relationship between trust in the leader figure and the perceived effectiveness of technologically enabled leadership.

In this model, the significance of the variable Usefulness_AI is also observed, with a coefficient of 0.318 (standard error = 0.139, $p < 0.05$). This is the first time in the models analysed so far that the perception of usefulness of AI shows a significant direct influence in predicting AI_LDR. This finding might suggest that when perceived reliability of AI output is not central, subjective AI usefulness acquires a stronger role in the construction of perceived leader effectiveness.

The model as a whole shows an R^2 of 0.689, with an adjusted R^2 of 0.680, values that are in line with those observed in previous models and indicate good overall explanatory power.

In summary, this regression suggests that although the technical reliability of intelligent systems is certainly relevant for smooth operational functioning, it is not sufficient on its own to reinforce the perception of leadership. On the contrary, the trust relationship with the human leader and, increasingly, the perception of the practical usefulness of AI in supporting decision-making processes emerge as decisive.

3.3.6 Linear regression: Ethical and Privacy Perception of AI

The sixth and final regression model examined the role of perceived ethics and privacy protection by artificial intelligence systems (Ethics) in predicting the perceived effectiveness of AI-supported leadership (AI_LDR). Also in this model, as in the previous ones, the control variables Trust_LDR and Usefulness_AI were included.

As can be seen from Table 10, the coefficient associated with the variable Ethics is positive but not statistically significant, with a value of 0.097 and a standard error of 0.094. This finding suggests that, in the context analysed, the mere perception of ethical compliance and protection of privacy by intelligent systems does not exert a direct and relevant influence on the perception of leadership effectiveness. Although ethics is an increasingly central issue in the public debate on AI, the data indicate that it is not, on its own, a discriminating factor in the assessment of leadership quality.

	(1)
Intercept	-0.521
	(0.442)
Ethics_	0.097
	(0.094)
Trust_LDR	0.676***
	(0.142)
Usefulness_AI	0.255**
	(0.123)
R-squared	0.693
R-squared Adj.	0.684
N	104

Standard errors in parentheses.
$* p < 0.1$, $** p < 0.05$, $*** p < 0.01$

Table 10: Linear Regression - Ethical and Privacy Perception of AI

In contrast, trust towards the AI-supported leader (Trust_LDR) is once again confirmed as the most influential variable in the model, with a coefficient of 0.676, standard error of 0.142 and high significance ($p < 0.01$). This value, in line with all previous models, underlines the importance of the trust component towards the leader figure, regardless of the technical, organizational or value characteristics of the AI used.

The variable Usefulness_AI shows in this model a coefficient of 0.255 (SE = 0.123), significant at the 5% level ($p < 0.05$), confirming the emergence of a positive role of the perception of the usefulness of AI in the prediction of leadership effectiveness. This result, already observed in previous models, confirms that the subjective perception of AI usefulness is an important driver in the process of leadership legitimacy in digital environments.

The overall model has an R^2 of 0.693 and a corrected R^2 of 0.684, showing good overall explanatory power, perfectly in line with the results of the other models analysed.

To sum up, the last regression model reinforces the reading that interpersonal trust and the perceived usefulness of AI are determinants in the construction of effective leadership in automated contexts, whereas the ethical dimension, although relevant in other domains (regulatory, reputational), does not exert a direct impact on the dependent variable analysed in this study.

3.3.7 – Analysis of the role of transparency and perceived ethics in artificial intelligence on trust in leadership

To further explore the research hypotheses outlined in Chapter 2, this section introduces an additional regression model aimed at testing hypothesis H2, which states that:

"The perceived transparency and ethicality of AI use by leaders positively influences the level of trust placed in the leader."

With a view to empirically exploring the association between leaders perceived responsible use of artificial intelligence and the level of trust among employees, a multiple linear regression model was developed to estimate the joint influence of two key dimensions: perceived transparency and perceived ethics. This study is part of theoretical hypothesis H2, according to which transparency and ethics in the use of AI can affect Trust in AI-Driven Leadership.

In the estimated model, the dependent variable is Trust_LDR, while the two independent variables are Transparency_ and Ethics_, constructed from multiple scales already validated in the literature. The regression, that can been observed in Table 11, shows good overall explanatory power: the coefficient of determination R^2 stands at 0.467, indicating that approximately 47% of the variance in trust in leadership is explained by the two predictive variables. The adjusted value of R^2 (0.456) also confirms the robustness of the model in taking into account the number of predictors.

Both variables are statistically significant. The transparency dimension (Transparency_) has a coefficient of 0.492 with a very high level of significance ($p < 0.001$), while perceived ethics (Ethics_) has a coefficient of 0.253, which is also significant ($p < 0.05$). The coefficients suggest that an increase in the perception of transparency and ethical correctness in the use of AI by the leader is positively and distinctly associated with an increase in trust in the leader.

The diagnostic indicators of model quality (Omnibus test, Durbin-Watson, Jarque-Bera, skewness and kurtosis) are consistent with the assumptions of linear regression, and no elements emerge that suggest significant violations.

In light of these results, the model provides a useful empirical framework for the theoretical reflection proposed in Chapter 2, laying the foundations for a more detailed discussion that will be explored in the next section of this paper.

	Trust_LDR	Transparency_ + Ethics_
Intercept	1.435***	
	(0.414)	
Transparency_	0.492***	
	(0.108)	
Ethics_	0.253**	
	(0.101)	
R-squared	0.467	
R-squared Adj.	0.456	
N	104	

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Role of transparency and perceived ethics in artificial intelligence

3.3.8 – AI adoption and managerial competence

In the proposed conceptual model (see Table 12), the construct "AI-enabled managerial skills" is theorised as an emerging capability driven by the adoption of AI tools in decision-making. Although previous models focused mainly on the dependent variable AI_LDR (AI-driven leadership effectiveness), the present analysis shifts the focus to the construct Competence_AI, treated as a dependent variable. The aim is to verify whether higher levels of Adopt_AI, i.e. the perceived degree of AI integration in managerial workflows, predict higher levels of digital and strategic competence in project-based contexts.

A simple linear regression model was estimated, with Competence_AI as the outcome and Adopt_AI as the sole predictor. The results are reported below.

The analysis returns a statistically significant and robust model ($F(1,102) = 124.1$, $p < 0.001$), an adjusted R-squared of 0.544, so the independent variable explains more than half of the the dependent construct shows an unreasonably high level of variance which is unusual for studies on behavior. The regression coefficient of Adopt_AI equals 0.6408 while maintaining $p < 0.001$

significance with a narrow confidence range of [0.527, 0.755]. The positive relationship between AI tool integration and manager perception of digital and strategic capability becomes evident through the coefficient value of 0.6408. The Durbin-Watson score of 2.081 indicates excellent residual behavior in the model while the residual distribution maintains OLS assumption boundaries despite its kurtosis value of 8.430.

The study validates H3 because it proves that AI implementation in managerial decision-making generates new competencies. The study demonstrates that AI integration effectiveness creates operational process changes which simultaneously promote digital environment leadership development.

	Competence_AI	Adopt_AI
Intercept	2.304***	
	(0.274)	
Adopt_AI	0.641***	
	(0.058)	
R-squared	0.549	
R-squared Adj.	0.544	
N	104	

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: AI adoption and managerial competence

3.4 Introduction to Mediation Models

The previous section examined how AI adoption and transparency and digital competence and systems trust and trustworthiness and ethics influence AI-supported leadership effectiveness (AI_LDR) through leader trust (Trust_LDR) and AI technology usefulness (Usefulness_AI) as control variables. The research revealed significant patterns but more studies are required to verify the indirect effects that appeared in the data.

Mediation models serve as statistical tools which enable researchers to identify the exact mechanisms through which different explanatory factors generate their observed effects.

In other words, while regressions tell us 'whether' a predictor has an effect, mediation models tell us 'how' this effect translates into perceived leadership effectiveness.

In our case, two theoretically relevant paths were developed as simple mediations:

- The former hypothesises that trust in the leader (Trust_LDR) acts as a mechanism through which the adoption of AI in decision-making processes (Adopt_AI) results in greater perceived effectiveness.
- The second model suggests that the perceived usefulness of AI (Usefulness_AI) mediates the link between systems transparency (Transparency) and perceived leadership.

Through the use of bootstrapping and the estimation of indirect effects with robust confidence intervals, these models make it possible not only to verify the significance of the mediated pathways, but also to estimate the extent to which the total effect of each predictor is conveyed by these mediators, thus offering a more nuanced and realistic view of the underlying dynamics of the phenomenon of interest.

In the following subsections (*3.4.1 and 3.4.2*), we present the results for each model in detail, interpreting them in light of the general theoretical framework and the practical implications for governance and leadership in data-driven organizations.

3.4.1 Mediation model 1: The mediating role of Trust in AI-Driven Leadership

The first mediation model examined the role of trust in the leader supported by AI (Trust_LDR) as a mechanism through which the adoption of AI in managerial decision-making (Adopt_AI) influences the perceived effectiveness of leadership (AI_LDR).

The objective was to test whether, in addition to the direct effect, the adoption of AI tools by management could exert a significant influence through the building of a fiduciary bond between leaders and employees.

The results, indicated in Figure 2, reveal a strong and statistically significant partial mediation:

- There is a very strong positive relationship between Adopt_AI and Trust_LDR ($\beta = 0.666$, SE = 0.053, $p < 0.001$), and it suggests that increased adoption of AI is related to increased trust in the leader who adopts it.
- The change from Trust_LDR to AI_LDR is still more important with a greater coefficient ($\beta = 0.926$, SE = 0.068, $p < 0.001$), enhancing the argument that trust plays a fundamental role in the perception of leadership effectiveness.
- The overall effect of Adopt_AI on AI_LDR, when the mediator is not controlled, is 0.850 (SE = 0.049, $p < 0.001$).

- With Trust_LDR added to the model, the direct effect falls to 0.591 (SE = 0.072, p < 0.001), while the indirect effect is 0.258—significant (p < 0.001) with a confidence interval of [0.122, 0.427], which does not cross zero.

	path	coef	se	pval	CI[2.5%]	CI[97.5%]	sig
0	Trust_LDR ~ X	0.666	0.053	0.000	0.561	0.771	Yes
1	Y ~ Trust_LDR	0.926	0.068	0.000	0.792	1.061	Yes
2	Total	0.850	0.049	0.000	0.752	0.948	Yes
3	Direct	0.591	0.072	0.000	0.449	0.734	Yes
4	Indirect	0.258	0.077	0.000	0.122	0.427	Yes

Figure 2: Mediating role of Trust in AI-Driven Leadership

These results confirm that the adoption of AI not only acts as a technological lever, but results in a strengthening of the leader-collaborator relationship. Trust becomes the bridge that connects the leader's technological competence with the perception of his or her effectiveness, transforming a technical change into a tangible improvement in leadership.

From a theoretical perspective, the model offers empirical evidence in support of the idea that technological innovation must be accompanied by solid relational capital to produce real benefits. In the absence of trust, even high adoption of AI risks not generating a perceived improvement in leadership.

In summary, trust in the leader emerges as a strategic mediating variable: it is the factor that transforms the adoption of AI from a mere procedural innovation to a lever for cultural and relational change within the organization.

3.4.2 Mediation model 2: The mediating role of Usefulness of AI

The second mediation model analysed the relationship between the perceived transparency of artificial intelligence systems (Transparency) and the perceived effectiveness of AI-supported leadership (AI_LDR), considering the perceived usefulness of AI in managerial contexts (Usefulness_AI) as a mediating variable.

The objective was to test whether the transparency of intelligent systems, apart from having a direct impact on the perception of leadership, can also operate indirectly through the reinforcement of the perceived usefulness of the technology. The analysis was conducted by bootstrapping (5000 samples) with 95% confidence intervals to robustly estimate the significance of the indirect effect.

These results, illustrated in Figure 3, confirm a strong and statistically significant partial mediation scenario:

- The link between Transparency and Usefulness_AI is very strong and highly significant ($\beta = 0.877$, SE = 0.071, $p < 0.001$), meaning that the clearer and more explainable AI decision-making processes are, the greater is their perceived usefulness.
- Consequently, Usefulness_AI has a positive and consistent impact on AI_LDR ($\beta = 0.743$, SE = 0.075, $p < 0.001$), such that useful technology remains the strongest influence in facilitating leadership.
- The net effect of Transparency on AI_LDR is 0.851 (SE = 0.084, $p < 0.001$).
- As the mediator is introduced, the direct effect reduces to 0.498 (SE = 0.125, $p < 0.001$), while the indirect effect rises to 0.353 (SE = 0.123, $p = 0.001$), with a confidence interval of [0.132, 0.618], confirming its significance.

	path	coef	se	pval	CI[2.5%]	CI[97.5%]	sig
0	Usefulness_AI ~ X	0.877	0.071	0.000	0.736	1.018	Yes
1	Y ~ Usefulness_AI	0.743	0.075	0.000	0.595	0.891	Yes
2	Total	0.851	0.084	0.000	0.685	1.017	Yes
3	Direct	0.498	0.125	0.000	0.250	0.745	Yes
4	Indirect	0.353	0.123	0.001	0.132	0.618	Yes

Figure 3: The mediating role of Usefulness of AI

These results demonstrate that both directly and indirectly, perceived transparency of AI systems impacts performance as a leader through perceived usefulness. In short, not only do open decision-making processes in AI build trust and acceptability of the technology, but they also increase its perceived value, which acts as a factor in determining legitimacy as a leader.

Theoretically, this model is a better version of the other (trust role-centered) because it emphasizes the cognitive dimension: whereas in the first case the lever is relational, in this case the driver of change is perception of usefulness. This means that, in organizations undergoing digital transformation, leadership is enhanced not only by open smart systems but also by their ability to yield tangible returns valued by stakeholders.

3.5 – Interpretation and discussion of statistical results in the context of leadership theory

After presenting the statistical analyses in detail, this section shifts the focus from description to interpretation, with the aim of situating the empirical results within the broader framework of leadership theory. While the previous sections have illustrated the descriptive trends, the correlational structures, and the predictive models obtained through regressions and mediations, the present discussion seeks to connect these findings to the conceptual debates outlined in Chapter 1.

The guiding principle of this section is that numbers acquire meaning only when read in light of theory. Accordingly, each set of results is interpreted in relation to established contributions from the literature on technology acceptance, trust in leadership, AI ethics, and digital transformation. The interpretive scholarship helps us show how experimental evidence matches theoretical predictions while revealing extra complex factors which improve our comprehension of AI-mediated leadership.

The discussion follows a thematic structure to evaluate how AI adoption impacts leadership performance and managerial skill development and transparency and ethical standards for trust creation and system reliability and usefulness and cognitive and relational processes that emerge from mediation analysis. The research investigates Project-Based Organizations (PBOs) because their organizational design presents both the greatest barriers and opportunities for AI system integration.

3.5.1 – AI Adoption and Leadership Effectiveness: from operational support to strategic leverage

The data presented in Section 3.3.1 demonstrates that AI tool implementation in management choices results in enhanced AI-based leadership effectiveness (AI_LDR). The regression model demonstrates a robust positive connection between AI adoption levels and organizational member ratings of leadership effectiveness because the coefficient shows significance and the R^2 value reaches above 0.70. The research shows that managers who use AI-based systems in their work activities get better ratings for their leadership performance. The study establishes through this essential finding that digital leadership transformation requires adoption as its core foundation.

The Technology Acceptance Model (TAM) by Davis (1989) and Venkatesh and Davis (2000) confirms these results because it demonstrates that perceived usefulness acts as a key factor for technology adoption. The empirical model demonstrates that AI adoption results in higher leadership legitimacy because leaders who use AI gain better assessments of their effectiveness and competency and their ability to achieve strategic organizational goals. The study confirms the e-leadership and digital research (Avolio et al., 2014) which demonstrates how technology functions as a transformative element for leadership practices and task creation.

AI adoption plays a crucial role in determining leadership effectiveness within Project-Based Organizations (PBOs). The temporary nature of PBOs together with their dynamic teams and unpredictable environment creates coordination problems and excessive information which AI enables leaders to handle. AI delivers two essential benefits to these scenarios through its ability to automate standard operations and generate predictive outcomes and optimize resources which allows leaders to tackle complex situations and detect threats and distribute resources more effectively. The research confirms that smart technologies enhance leadership capabilities according to project management and AI literature which views them as structural additions rather than replacements (Faraj et al., 2018; Raisch & Krakowski, 2021).

The research demonstrates that AI implementation produces advantages beyond operational efficiency because it changes how leaders perceive their authority and establish their legitimacy. Leaders who possess knowledge transform algorithmic outputs into strategic guidance through their decision-making abilities. Modern leaders now perform two functions as they combine human decision-making with technological advancements to create a hybrid leadership model.

3.5.2 – Managerial Competence Building and AI Adoption

The research demonstrates that AI implementation in managerial choices produces direct statistical evidence of positive outcomes (Adopt_AI)3.3.7 shows AI adoption enables substantial growth in managerial competency development and AI-based managerial competence belief (Competence_AI). The regression model in Section explains more than half of the dependent variable variation through its R^2 value of 0.549. The coefficient strength ($\beta = 0.6408$, $p < 0.001$) indicates that AI adoption functions as a capability development tool which helps managers acquire digital organizational competencies.

The research backs up current studies about e-leadership and digital leadership (Avolio et al., 2014) which prove how technology changes leadership duties by making managers link human teams to digital systems. Leaders must learn data literacy and algorithmic interpretation and digital sensemaking skills while building their communication and change management and facilitation competencies. The dual requirement shows how managerial work in AI environments combines two opposing aspects because leaders must understand data-driven intelligence and simultaneously direct group activities.

Raisch and Krakowski (2021) introduced the automation–augmentation paradox which demonstrates how AI executes repetitive operations while making human choices better through analytical strength and strategic insight. AI systems transform managerial capabilities through organizational changes which demand leaders to acquire competencies for algorithmic outcome evaluation and knowledge combination and management of socio-technical systems. AI implementation accelerates the transition from traditional command-and-control systems to leadership orchestration because leaders must now generate value by effectively managing human and technological resources and human resources.

The particular organizational framework of Project-Based Organizations (PBOs) makes this dynamic especially important. The short-term nature of PBOs combined with their shifting team composition and intricate project linkages requires organizations to focus on knowledge sharing and competence development as critical operational challenges. AI integration into decision systems improves project delivery performance while creating digital solutions for short-term teams and establishing ongoing learning processes that enhance organizational capabilities. The theoretical framework in Chapter 1 shows that PBOs stay competitive through their ability to maintain flexible structures which prevent competence accumulation. AI technology functions as a vital element to preserve equilibrium because it helps leaders transform project-specific knowledge into sustainable organizational capabilities.

Research findings and statistical data show AI functions as a transformative power that advances managerial growth instead of being viewed as a straightforward technological issue. Leaders who excel at AI integration in their decision-making process achieve superior management status because they master three critical functions which include capability development and technology interpretation and collective intelligence facilitation.

3.5.3 – AI-Based Leadership Trust, Ethics, and Transparency

The regression model in Section 3.3.8 demonstrates that transparency and ethics directly impact how much AI leaders are trusted by their followers (Trust_LDR). The study shows that transparency stands out as the leading factor for trust ($\beta = 0.492$; $p < 0.001$) while ethical perception shows a smaller but statistically significant effect ($\beta = 0.253$; $p < 0.05$). The two variables explain 46.7% of the dependent construct variance ($R^2 = 0.467$) which demonstrates that perceived governance capacity functions as a primary factor for AI-based leadership legitimation.

The study supports existing research which demonstrates that trust in leadership stands as a fundamental element for successful leadership. Dirks and Ferrin (2002) explain that trust functions as a vital leadership element which produces cooperative behavior and dedicated staff and superior performance. AI creates an additional challenge for trust development because employees need to trust both their human leaders and the technical systems that support decision-making. The study confirms Glikson and Woolley's (2020) theory that human-AI trust consists of two parts because people need to trust both the human leader's motives and the reliable operation of algorithms with transparent and just decision-making systems.

The results show that transparency produces a more significant impact on ethics than other factors. The essential ethical values of fairness and privacy and accountability remain important in theoretical discussions (Floridi, 2019; Jobin et al., 2019) yet employees prioritize clear understanding of AI operational processes above all else. The direct link between transparency and leader confidence stems from employee ability to understand AI decision-making processes. The effects of ethics become visible through specific governance and communication practices which translate its abstract framework into concrete actions.

The research findings support the theoretical framework from Chapter 1 which emphasizes explainable AI systems for effective governance. The lack of transparency in many AI systems leads to public doubt and opposition so organizations need to make their processes visible to establish trust. The digital governance literature shows how blockchain technology and smart contracts create transparent organizational processes which build trust for both leaders and all decision-making systems. The research findings support the empirical results by showing that transparency functions as a relationship-based asset which enhances leadership legitimacy although this aspect was not directly measured in the study.

Research indicates that trust operates through relational currencies which include ethics and transparency where transparency directly affects trust while ethics provides underlying legitimacy. The study demonstrates that AI-mediated trust operates through technological communication systems instead of personal authority or charismatic leadership. Decision-makers who provide transparent AI decisions supported by ethical justifications gain greater legitimacy which strengthens their digital organizational power base.

3.5.4 – Reliability, Ethics, and the Perceived Effectiveness of Leadership

The analysis of AI-based leadership performance (AI_LDR) through perceived reliability and ethicality regressions produced inconsistent results which were less significant than those found for adoption and transparency and usefulness. The positive coefficients of these constructs indicate employee acceptance of reliable and ethical AI systems yet their actual impact on leadership performance assessments remains uncertain.

The results indicate a significant difference between what employees perceive in practice and what scholars consider essential for responsible AI implementation. The academic field of AI governance identifies ethics and reliability as essential elements for proper intelligent system implementation. The scholarly work of Floridi (2019) and Jobin et al. (2019) demonstrates that accountability together with fairness and technical reliability serve as essential elements for trustworthy AI systems. The absence of clear ethical standards and unreliable system outputs directly challenges both leadership authority and organizational legitimacy.

Yet our results indicate that these variables, while directionally positive, are less predictive of leadership effectiveness than transparency, trust, or adoption. One plausible explanation is that reliability and ethics are assumed, assumed implicitly by employees rather than explicitly evaluated. That is, partners may take for granted that organizational systems need to be ethically and technically correct, and so do not overtly reward these qualities when judging leadership. The emergence of negative leadership perception determinants would need a failure of reliability or ethics through errors or bias or remain in experimental stages of AI adoption according to Chapter 1 because they prioritize operational efficiency over developing comprehensive abuse.

The current stage of organizational AI adoption maturity explains why these differences exist. The majority of businesses ethical frameworks and system reliability testing. The employees focus on direct governance elements such as transparency and communication because they can see their impact on leadership effectiveness while reliability and ethics remain important but harder to notice.

The comparatively weaker effects of reliability and ethics compared to the remaining constructs should not be construed as a demonstration of their irrelevance. Rather, they highlight the distinction between latent normative expectations and salient relational drivers. Reliability and ethics are essential “hygiene factors” in AI-enabled contexts: they may not directly boost leadership legitimacy when present, but their absence or violation could severely erode it. This interpretation calls for organizations to embed ethics and reliability not only as technical backstops but also as communicated practices, ensuring that these values are visible and integrated into leadership behaviours.

3.5.5 – Cognitive and Relational Mediation Pathways: Usefulness and Trust as AI Influence Channels

The models presented in Section 3.4 demonstrate that AI affects effective leadership through two separate yet harmonious pathways which start with cognitive perception of AI system usefulness and build trust in AI leadership. The legitimacy of AI-assisted leadership develops through the combination of technical achievements with social approval.

The mediation model demonstrates that output reliability and transparency strengthen workers' perception of AI usefulness which directly improves leadership effectiveness. The Technology Acceptance Model (TAM) by Davis (1989) and Venkatesh & Davis (2000) demonstrates that usefulness acts as a key factor which drives technology adoption. Workers will view their leader as effective when they understand AI systems because these systems present clear and useful decision-making assistance. The cognitive mediation process shows that AI needs workers to understand its practical value before it can transform into better leadership credibility.

The second mediation path from the relational perspective shows that AI adoption and governance practices lead to increased trust in AI-led leadership which subsequently influences how people view leadership effectiveness. The pathway upholds leadership relational principles from Dirks and Ferrin (2002) and Yukl (2013) because trust operates as a social resource which enables teamwork and brings people together for shared objectives. AI trust surpasses personal leader trust because it includes the social-technical frameworks which leaders build and sustain (Glikson & Woolley, 2020). Leaders who achieve success in converting technology adoption into relational legitimacy show both responsibility and accountability and prompt response abilities when deploying AI systems.

The research findings validate the theoretical model from Chapter 1 which explains digital leadership as an integration of automated systems with human choices and technological optimization with clear management practices. AI influences human conduct through dual mechanisms which combine logical decision-making abilities with trust-based acceptance of authority. AI modifies leadership principles instead of removing them because digital leadership success depends on leaders who unite their technical skills with their ability to establish trust-based connections.

The two fundamental multipliers that drive leadership success in AI-driven organizations are usefulness and trust. The cognitive channel ensures that AI is seen as functionally useful, and the relational channel ensures its application is socially accepted and legitimized. The synergy of these channels ensures that the development of leadership in the age of AI unfolds through integration, as opposed to substitution, and positions leaders as orchestrators of both data-driven insights and social sense-making.

3.5.6 – Specificities of Project-Based Organizations: Temporariness, Knowledge Transfer, and Leadership Roles

The analysis of statistical findings becomes more comprehensive when researchers place them within the organizational framework of Project-Based Organizations (PBOs). The organizational structure of Project-Based Organizations (PBOs) presents distinct leadership and knowledge management challenges because of their temporary nature and project-based teams and high task dependencies as described in Chapter 1. The organizational structure of PBOs differs from traditional functional organizations because they use short-term resource combinations under urgent deadlines and unpredictable environmental conditions.

AI tools achieve their highest level of value during these specific situations. AI maintains cognitive continuity between projects through information storage and processing which enables knowledge sharing and prevents the common loss of team work capabilities. The feature enables researchers to study organizational learning in temporary systems because it demonstrates methods to preserve and utilize knowledge within non-continuous operational frameworks. AI systems enhance control and coordination functions at reduced information overload expenses while delivering faster decision-making capabilities. The system reduces traditional project work transaction costs which studies on temporary organization governance have identified.

AI implementation changes how leaders function within PBOs. Leaders now function as system orchestrators who unite human capabilities with technological resources instead of focusing solely on project delivery. Leaders must convert algorithmic data into technical information and simple explanations which team members can comprehend. The implementation of AI technology creates two essential duties for PBO leaders who must link temporary teams through knowledge transfer and build trust during fast-paced organizational changes.

The research shows that PBOs need leaders who possess both standard management competencies and capabilities to handle digital infrastructure and AI deployment for success in short-term settings. AI technology helps PBOs transform their natural structural disadvantages of discontinuity and fragmentation and uncertainty into opportunities for enhanced coordination and leadership development and sustained organizational legitimacy.

3.5.7 – Summary of findings

The research methods outlined in this chapter enable scientists to evaluate the complete impact of artificial intelligence on project-based organizational leadership. The research shows how AI affects leadership perception and practice through two essential elements which consist of AI system cognitive value and trust and legitimacy as relational factors.

The cognitive perspective operates through three mechanisms which include perceived usefulness and transparency and output reliability. Leaders who produce superior outcomes implement AI tools that merge technological resources with decision systems which produce unbiased results and straightforward solutions. AI operates as a cognitive amplifier which enhances sensemaking abilities and coordination performance when dealing with complex and unpredictable situations.

The two core components of relational leadership in AI consist of trust-based AI leadership and ethical guidelines that control technological implementation. Leaders obtain legitimacy through their implementation of AI technology which they embed into governance systems to receive public backing for their algorithmic choices. Trust acts as a relationship builder that enhances individual and group performance to improve teamwork and team member commitment which results in superior leadership program outcomes.

The research supports the argument that AI transforms leadership principles instead of replacing them. Leaders in digitalized project-based organizations need to combine their technical skills with human judgment and their technical abilities with social validation to achieve success. Leaders now operate as system orchestrators who maintain equilibrium between automated processes and human connection to manage socio-technical systems.

The research conducted in this chapter demonstrates that AI era leadership development needs new methods to work alongside established practices instead of eliminating them. AI functions as a mental tool which builds connections to enhance leadership competencies and professional trust within project-based work settings.

Chapter 4 – Discussion of Results and Hypotheses Verification

4.1 Hypotheses Discussion

4.1.1 – Hypothesis 1: AI Adoption and Leadership Effectiveness

The first hypothesis stated that leaders who use AI tools will report superior project leadership outcomes according to their self-assessment. The empirically established results provided in

Section 3.3.1 also support this assumption to a great extent. The regression model revealed a strong and highly significant relationship between the degree of AI adoption (Adopt_AI) and the effectiveness in leadership created by AI (AI_LDR), and an explanatory power (R^2 higher than 0.70) that reflects the strong role played by adoption in constructing good leadership perceptions.

The results support the Technology Acceptance Model (TAM) by Davis (1989) and Venkatesh and Davis (2000) because perceived usefulness serves as the key factor for evaluating new technology adoption. Managers who lead the effort to implement AI in decision-making earn respect for their competence and goal achievement because they show how to transform technological capabilities into operational solutions. The research findings validate the concepts which Avolio et al. introduced in their studies about e-leadership and digital literature analysis. Boudreau and Ramstad (2014) demonstrate in their paper that technology operates as an operational resource which transforms leadership duties and modifies organizational power systems.

AI functions in Project-Based Organizations (PBOs) operate as operational tools to automate processes and generate forecasts and strategic instruments which leaders use to handle complex situations and preserve organizational legitimacy because PBOs experience elevated coordination expenses from their unpredictable environment and brief team periods. AI technology produces two effects which demonstrate its ability to boost leadership performance through enhanced sensemaking and coordination and authority management.

The research supports hypothesis 1 because it demonstrates that AI implementation directly influences project success when digital technology plays a crucial role in project operations.

4.1.2 – Hypothesis 2: Transparency, Ethics, and Trust in Leadership

The research tested the hypothesis that leaders who demonstrate transparent and ethical AI practices will receive higher levels of trust from their followers. The regression analysis in Section 3.3.8 demonstrates strong evidence which confirms this assumption. The study revealed that ethics and transparency serve as powerful indicators which explain 46.7% of the Trust in AI-Driven Leadership (Trust_LDR) dependent variable variance ($R^2 = 0.467$). Transparency, in particular, produced a highly significant and stronger effect ($\beta = 0.492$, $p < 0.001$), while ethics had a weaker, but positive and statistically significant effect ($\beta = 0.253$, $p < 0.05$).

The research findings support previous studies which show trust in leadership stands as a core requirement for effective leadership (Dirks & Ferrin, 2002). The complexity of trust in AI-mediated environments increases because it requires trust in both the individual leader and the technical systems which support decision-making processes. The dual nature of trust in AI systems matches Glikson and Woolley (2020) who explain that users must trust both the intentions of leaders and the reliable and unbiased functioning of AI algorithms.

The more salient place of transparency above ethics describes a large subtlety. The fundamental ethical principles of fairness and privacy respect and accountability continue to be vital in modern normative discussions (Floridi, 2019; Jobin et al. 2019), employees appear to value more the visible and explicable AI processes in which they work. Players develop trust in their leader through AI decision-making transparency because they can observe the reasoning that drives each choice. The ethical framework operates as an implicit standard which people become aware of through the actions of those who violate it.

Project-Based Organizations (PBOs) must start AI system implementation immediately because their short-term teams need to establish trust right away. Leaders who disclose their algorithms and operate under ethical standards will develop the relational capital required to execute projects effectively.

The confirmation of hypothesis 2 supports the theory that AI-driven leadership trust depends on both achievement results and the transparent ethical systems which produce these results.

4.1.3 – Hypothesis 3: AI Adoption and Managerial Competence

Hypothesis 3 posited that AI adoption by managerial decision-making processes has the result of generating new managerial competences required in order to be able to operate in digitalised environments. The regression model from Section 3.3.7 demonstrates powerful empirical evidence which supports this hypothesis. There is a robust association between Adopt_AI and Competence_AI ($\beta = 0.6408$, $p < 0.001$), and the model explains over half of the variance of the dependent construct ($R^2 = 0.549$). The research shows that AI implementation serves as a major capability builder which enhances both operational performance and leadership competencies.

The research results confirm the theoretical models which e-leadership research has established (Avolio et al. Kallio (2014) demonstrates in his article that technological integration changes management work so leaders need to link digital systems with human operations. Managers need to acquire data literacy and algorithmic interpretation and digital sense-making abilities to implement AI yet they must also develop essential soft skills for communication and change management to integrate into their operational framework. The leaders must hence carry a hybrid persona and play both the roles of data-based fact interpreters and facilitators of collective intelligence.

The study results confirm the automation–augmentation paradox which Raisch and Krakowski (2021) described. AI adoption enables managers to enhance their competence through its strategic and analytical capabilities which leaders can apply to their work. The automation process through AI generates increased need for human skills to assess and combine and confirm the results produced by algorithms. The system creates an equal balance between positive and negative effects on management work because it eliminates basic supervision tasks but demands advanced capabilities for critical thinking and socio-technical system management and strategic planning.

Project-Based Organizations (PBOs) need to develop competence to achieve higher operational significance. Project teams need to transfer knowledge and acquire skills quickly because their teams exist only temporarily and change frequently. Leaders who use AI in their decision-making process function as capability multipliers because they distribute digital competencies to their team members while building organizational knowledge for the future through project-based learning. The research results support the theoretical framework established in Chapter 1 which shows PBO leaders need to fulfill two essential duties for short-term work coordination and long-term competency development.

The evidence supports hypothesis 3 because AI adoption leads to the development of managerial competencies which enable digital transformation in project management environments.

4.1.4 – Hypothesis 4: Leadership Effectiveness, AI Adoption, and Strategic Consistency

Hypothesis 4 assumed that the extent of adoption of AI in organizational procedures is positively related to both effectiveness perceptions of leadership and strategic consistency. The evidence from Chapter 3 shows that this hypothesis has some basis for truth. The results from Section 3.3.1 show AI adoption leads to better leadership effectiveness but the data collection does not include a direct measure for strategic consistency.

The research design produced this partial outcome which demonstrated both the positive and negative aspects of the study. The collected data confirms that AI implementation produces superior leadership effectiveness which proves the prediction about leaders who use AI for decision support achieving higher ratings for legitimacy and capability and effectiveness. The study fails to include a specific variable which would measure AI adoption effects on long-term strategic direction thus blocking complete evaluation of the second part of the hypothesis.

The research discovery opens up fresh avenues for theoretical investigation. The research by Henderson and Venkatraman (1993) and El Sawy et al. (2016) along with Author's Last Name (2016) demonstrates that technology implementation success requires organizations to develop a strategic vision which defines the core purpose of the technology. The main challenge for project-based organizations with their short-term goals and temporary structures lies in implementing AI within specific projects while maintaining connection to broader organizational targets. The study provides partial evidence for H4 which reveals a major theoretical gap because researchers need to investigate how AI adoption creates value for strategic alignment improvement.

The study does not contain a specific variable to assess AI adoption effects on long-term strategic direction which hinders complete evaluation of the second part of the hypothesis.

The research supports hypothesis 4 to some degree. The study confirms that AI implementation produces superior leadership outcomes but it does not provide direct proof about how AI adoption affects strategic fit alignment. The study maintains its value because it demonstrates the requirement for additional research that would develop specific methods to track AI integration approaches in short-term adaptable PBO organizational settings.

4.2 – Comparison with the Literature

The research outcomes align with existing scholarly debates about leadership and digital transformation by supporting established theories while introducing new perspectives. The research design allows scientists to confirm existing knowledge through new data acquisition from organizational projects.

The study confirms the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000) because staff members base their technology acceptance on perceived usefulness. The research supports this perspective because leaders who implement AI in decision-making processes gain better status through their ability to convert technological adoption into concrete advantages for their team members. The research results confirm the findings presented by Avolio et al. (in their e-leadership and digital literature. The research by Orlikowski and Scott (2014) demonstrates that digital infrastructure turns leadership into a role of socio-technical system management instead of making it obsolete. AI operates as a system which boosts leadership performance instead of making leadership unnecessary.

Research studies confirm the research findings about ethics and transparency and trust through multiple investigations. Dirks and Ferrin (2002) identify trust as the essential factor which makes leadership legitimate. Glikson and Woolley (2020) confirm that employees in AI-enabled environments require trust in both their human leaders and the algorithmic systems used for decision-making.

Research findings show that transparency leads to increased trust levels than ethical perception does which shows a small yet important change from past AI ethics research. While Floridi (2019) and Jobin et al. (2019) stress that fairness, accountability, and privacy are preconditions for trustworthy AI that are not negotiable, the workers seem to value most of all what they can see and understand. Organizations demonstrate their legitimacy through transparency but ethicality remains the fundamental requirement which becomes most apparent when organizations violate their ethical principles. The method follows ethical principles because it shows how to turn ethical standards into practical organizational methods which match regular business activities.

The theory of competence development converges with AI adoption at this point. The relationship between adoption and management skills proves the automation–augmentation paradox which Raisch and Krakowski (2021) explain through AI's dual capability to automate tasks and train managers for technical and analytical and relational competencies. Our results are in line with this paradox, demonstrating that the more leaders embrace AI, the more they must establish skills in data literacy, interpretation of algorithms, and communication. The obtained result indicates that AI will not replace managers in their work activities which makes it harder to support the substitution threat theory for managerial positions. AI technology requires leaders to develop superior abilities which leads to increased expectations for leadership competencies.

The research findings show some differences from the current theoretical frameworks. The research findings show that ethics and dependability have less impact on leadership performance than transparency and trust according to the study. The literature shows that staff members consider these elements as organizational necessities which become apparent only when they vanish or fail (Floridi, 2019). The ongoing organizational operational conflicts with academic and policy-based ethical standards demonstrate that workers experience governance signals more directly than ethical standards. Academic theory requires better comprehension of the “translation gap” which exists between theoretical ethical frameworks and actual organizational member experiences.

The results gain more importance because they occur within the framework of Project-Based Organizations (PBOs). Digital transformation research focuses on permanent functionally organized businesses yet PBOs present unique challenges because of their short-term operations and limited knowledge base and urgent need for trust development. AI implementation enables cognitive continuity through knowledge storage and foresight generation which also establishes relational legitimacy through transparent operations that enhance current digital change theories through adaptable organizational structures. The research findings show how general leadership principles connect to the distinctive elements which define project-based work settings.

Research supports existing theories about technology adoption and trust and e-leadership yet presents new perspectives which enhance our understanding of these concepts. The results surpassed expectations while minimal variations in ethics and performance based on context emerged which indicates that theories need to understand how employees really interact with AI systems at work. AI leadership in the modern era demands more than technical deployment because it requires creating acceptable AI adoption behaviors that foster productive teamwork through human relationships.

Chapter 5 – Conclusions, Implications and Future Directions

5.1 – Opening Remarks

The research examined how artificial intelligence implementation transforms modern organizational leadership practices with special emphasis on Project-Based Organizations (PBOs). The research used descriptive analysis and correlation patterns and regression models and mediation tests to show how AI impacts leadership through cognitive and relational changes which enhance effectiveness perceptions and competence and trust.

It is possible to think of different types of fundamental conclusions. First, leadership performance is driven by AI adoption, confirming that leaders who integrate intelligent systems into the decision-making process are also perceived as being more legitimate and competent. Second, adoption not only affects outcomes but also prompts the creation of new managerial competencies, in accordance with the notion that AI extends but does not replace human abilities. Third, the research points to the relational underpinnings of leadership: ethics and transparency contribute heavily to trust-building, with transparency having a more significant and conspicuous impact. Lastly, the mediation analyses identify that AI influence is mediated through perceived usefulness and trust, ascertaining that leadership change in the digital era progresses through integration, rather than replacement.

The research findings produce significant implications for future work. The study applies the Technology Acceptance Model (Davis, 1989; Venkatesh & Davis, 2000) and leadership theories based on trust (Dirks & Ferrin, 2002) to show how leaders' legitimacy and competence affect technology adoption. The authors stress that organizations and managers should handle AI as an intelligent system which needs organizations to show their governance practices and develop competence and sustain transparency.

The study acknowledges its limited participant pool and its cross-sectional research approach and missing construct measurements yet provides a starting point for subsequent investigations that can use longitudinal designs and multiple research methods and direct assessments of strategic alignment and AI resistance.

The available evidence supports the conclusion that AI transforms leadership rather than eliminating it. Leaders who succeed in digitalized and project-based environments merge artificial intelligence with human intuition and combine technical abilities with interpersonal trust and immediate project results with sustained professional growth. Leaders in the AI era serve as system managers who demonstrate technology operations to stakeholders and achieve its benefits through their specialized knowledge.

The research establishes that future leadership requires uniting human intelligence with artificial intelligence instead of fighting against AI or surrendering control to algorithms. The research identifies key sustainable leadership elements by studying the intersection of human intelligence and artificial intelligence in organizations.

5.2 – Theoretical and Practical Implications

The research findings from this study enable the advancement of leadership theory and better digital management practices in organizations. The research examines how AI implementation impacts leadership capabilities and performance and trust dynamics and governance systems to determine its effects on project-based leadership fundamentals.

5.2.1 – Theoretical Implications

From a theoretical standpoint, the study contributes to ongoing debates on technology acceptance and digital leadership. First, the strong link between AI adoption and leadership effectiveness reinforces the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000), but extends it by showing that perceived usefulness does not only legitimise the technology itself, but also enhances the legitimacy of leaders who champion it. In this sense, TAM is broadened from a purely individual-level adoption framework to a leadership-level lens, where leaders embody the role of mediators of technology legitimacy.

The findings advance the literature on trust in leadership (Dirks & Ferrin, 2002) and human–AI trust (Glikson & Woolley, 2020), showing that trust emerges as a dual construct: employees must trust both the leader and the AI systems they deploy. The stronger impact of transparency compared to ethicality highlights a refinement to existing theory: while ethics is normatively fundamental (Floridi, 2019; Jobin et al., 2019), employees prioritise visible practices of explainability over abstract ethical assurances. This suggests that theories of trust and AI ethics should more explicitly consider the translation gap between normative principles and everyday organizational perceptions.

The evidence contributes to the debate on the automation–augmentation paradox (Raisch & Krakowski, 2021). Rather than eroding leadership roles, AI adoption stimulates the development of higher-order managerial competences, repositioning leaders as orchestrators of socio-technical systems. The research refines the complexity leadership theory which Uhl-Bien et al. 2007), by emphasising that effective leadership in digitalised environments depends less on hierarchical authority and more on the integration of cognitive (usefulness, reliability) and relational (trust, transparency) foundations.

The contextualisation in Project-Based Organizations (PBOs) advances the literature by showing how digital transformation operates under structural temporariness. The research shows that AI implementation reduces the knowledge gaps and relationship instability which are common in PBOs thus enhancing our knowledge about leadership in short-term organizational structures.

5.2.2 – Practical Implications

The research findings offer management team members various useful suggestions for implementation. Managers need to view AI as more than an efficiency tool because it functions as relational capital which supports their organizational legitimacy. AI-supported decision transparency along with governance systems that ensure transparency must be implemented to build trust between stakeholders.

Organizations need to create formal competence development programs because AI deployment requires them to do so. Leaders need training investments that extend past technical skill development to include data literacy and critical thinking and communication skills which enable them to understand algorithmic results and explain them effectively to others.

The management of PBO projects depends on AI technology for project execution and knowledge retention systems. AI technology integration into project work enables managers to create learning experiences from brief projects which stops knowledge from getting lost in different areas.

Organizations should not depend on implicit trust because research shows no direct relationship between ethics and reliability and trust levels. The AI tools and open book reporting and blockchain-boosted audit trails to demonstrate compliance and fairness. Open book practices for ethical and reliable AI usage help managers build trust and create organizational legitimacy. process of ethical standards and reliability testing demands complete openness through exact communication systems. The system needs explainable

5.3 – Study Limitations

The research contains specific boundaries which need identification to achieve proper result interpretation and establish future research directions. The research findings maintain their value because they define specific boundaries for result interpretation. The research faces its first challenge because the participant numbers stay restricted while their ability to represent the population remains unclear. The survey achieved 104 usable responses which supported statistical analysis yet the participant pool remained restricted to specific industry sectors and professional organizations which reduces generalizability to all organizational settings. The research findings from this study cannot be directly applied to different contexts because the participants came from specific industry sectors and professional organizations. The research needs to expand its participant base to include participants from various sectors and cultural backgrounds for future studies to achieve better results.

The research contains specific boundaries which need identification because they affect proper interpretation of results and create new directions for upcoming investigations. The results maintain their value because they define specific boundaries for understanding their findings.

The study faces a limitation because it uses a cross-sectional research approach. The study's one-time measurements prevent researchers from establishing cause-and-effect relationships between variables. The regression and mediation analysis results demonstrate that succession affects AI adoption yet they fail to show which factor occurs first in the sequence of events. The study needs longitudinal research methods to monitor how these relationships transform as organizations progress through their digital transformation process.

The measurement scope of the construct represents one-third of the total limitations. The dataset lacked concrete variables which made it impossible to operationalize strategic consistency as an element of H4 and resistance to AI adoption. The research team conducted limited verification of some hypotheses because they could not test them in their complete form. The study would benefit from additional analysis which would enable researchers to conduct more comprehensive testing of the research model through expanded measurement instruments that include these dimensions.

The study faces its fourth limitation because scientists need to depend on participant self-reports for their research. Self-report measures are commonly used in organizational studies but they present two major limitations because they can be influenced by social desirability bias and common method variance. The participants gave ratings about AI adoption and transparency and leadership effectiveness which might have shown higher or lower levels than their actual beliefs. The evaluation of survey data requires additional objective performance measures together with interviews and ethnographic observation to validate findings about studied phenomena.

The research findings remain limited to their specific context. The research on Project-Based Organizations (PBOs) provides vital information about leadership in short-term adaptable organizations yet these findings do not directly translate to traditional functionally organized businesses. The three PBO-specific characteristics of temporary nature and knowledge discontinuity and fast trust development make PBOs highly susceptible to AI adoption which could explain the observed significant effects. Research should focus on different organizational structures to determine if these patterns exist in various business environments.

5.4 – Future Research Directions

The research presents multiple directions for future investigation which will enhance and expand the findings of this study. The research on AI-enabled leadership through various approaches requires investigation of methodological and theoretical and practical aspects because of AI's complex multifaceted nature.

Research needs to expand its sample size while incorporating participants from different sectors and management systems and cultural backgrounds to achieve complete industry-wide assessment. The study would help researchers understand if PBOs generate their exceptional results through typical organizational conditions or because of their unique combination of short-term status and disrupted knowledge flow and high interdependence. The research that studies both short-term and long-term forms will generate the most valuable findings.

The first research approach for scientists requires them to perform studies using longitudinal research designs. The research of AI adoption and digitalization requires studying how leadership perceptions and trust and competency levels change throughout time because these processes function as dynamic systems. Research on leaders and organizations through longitudinal studies allows scientists to track their development across different stages of AI implementation which shows both short-term and long-term effects on leadership approaches and organizational power structures.

Future research needs to focus on operationalizing the underdeveloped constructs as a third research direction. The measurement of Strategic consistency as hypothesis 4's element needs direct assessment together with other constructs that affect AI adoption resistance. The conceptual model evaluation would gain fullness through the addition of these dimensions because they expose new elements which affect AI legitimacy in leadership positions.

The fourth approach to progress involves using multiple research approaches. The current research relies on survey data and quantitative methods yet future investigations need to use qualitative approaches including interviews and case studies and ethnographies to study AI system interactions between leaders and employees in actual workplace settings. Research that combines statistical generalisability with contextual depth through mixed-methods approaches enables researchers to achieve a more complete understanding of their findings.

The fifth direction for future development focuses on ethical and governance frameworks. The research should concentrate on creating workplace conduct based on ethical principles because employees follow transparency better than ethics and reliability when achieving results. The research should prioritize the development of explainable AI tools and blockchain-based accountability systems and formal audit procedures which help organizations show their ethical compliance.

The research needs to explore how competence development affects real-world operations. Research should focus on how AI systems affect training infrastructure and workplace culture and leadership development systems to build sustainable managerial competencies. The research investigates these relationships because project-based work environments struggle with developing short-term and unstable skills.

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